

Dynamics in two networks based on stocks of the US stock market

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Abstract

We follow the main stocks belonging to the New York Stock Exchange and to Nasdaq from 2003 to 2012, through years of normality and of crisis, and study the dynamics of networks built on two measures expressing relations between those stocks: correlation, which is symmetric and measures how similar two stocks behave, and Transfer Entropy, which is non-symmetric and measures the influence of the time series of one stock onto another in terms of the information that the time series of one stock transmits to the time series of another stock. The two measures are used in the creation of two networks that evolve in time, revealing how the relations between stocks and industrial sectors changed in times of crisis. The two networks are also used in conjunction with a dynamic model of the spreading of volatility in order to detect which are the stocks that are most likely to spread crises, according to the model. This information may be used in the building of policies aiming to reduce the effect of financial crises.

Keywords: financial markets; propagation of crises; correlation; transfer entropy.

JEL Classification: G1; G15.

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1 Introduction

The issue of the spreading of crises among financial markets has been a topic of intensive study, mainly after the crisis of 2008 and the subsequent crises. The mapping of the network of banks and other financial institutions is now considered essential to the understanding of how defaults can propagate from one institution to another, and understanding the network of financial institutions has been placed among the main challenges of the present (Haldane, 2009). This article contributes to a better understanding of a network based on stocks negotiated in the two main stock exchanges of the USA, that are also among the largest stock markets in the world: the New York Stock Exchange and the Nasdaq. In order to do so, we use two measures of how one stock relates to another: the Pearson correlation and Transfer Entropy.

The Pearson correlation, developed by Karl Pearson (1857–1936), measures how similar are the time series of two variables (stocks, in our case). Transfer Entropy (TE), developed by Thomas Schreiber (2000), is a measure of the amount of information that the time series of one variable has on the time series of another variable that was not already in the time series of the latter. The first measure, correlation, is symmetric and based on linear relations, although there are correlation measures, like the Spearman rank correlation and the Kendall tau rank correlation, that measure nonlinear correlations. The second measure, Transfer Entropy, is dynamic, non-symmetric, and is related to Granger causality, although it is not model-dependent, and is capable of detecting nonlinear relations between variables. Both measures are applied to 464 stocks negotiated

in the New York Stock Exchange and/or Nasdaq, from 2003 to 2012, in order to build networks of stocks. The evolution of these networks are then studied through time, and the dynamics of the relationships between stocks and between sectors are studied both from the point of view of similarity (using correlations) and of causality (using TE). The networks are also used, in conjunction with a model for the spreading of volatility, in order to detect, according to the model, which are the stocks more likely to spread crises.

There is an extensive literature on the propagation of shocks in networks of financial institutions, and describing all the published works in this subject is beyond the scope of this article. Most of the works in this field can be divided into theoretical and empirical ones, most of them considering networks of banks where the connections are built on the borrowing and lending between them. In most theoretical works (Kirman, 1997; Allen and Gale, 2000; Watts, 2002; Vivier-Lirimont, 2004; Leitner, 2005; Nier, Yang, Yorulmazer and Alentorn, 2007; Castiglionesi and Navarro, 2007; Cossin and Schellhorn, 2007; Lorenz, Battiston and Schweitzer, 2009; Schweitzer, Fagiolo, Sornette, Vega-Redondo, and White, 2009; Allen and Babus, 2009; Gai and Kapadia, 2010; Georg, 2010; Canedo and Martínez-Jaramillo, 2010; Gai, Haldane and Kapadia, 2011; Tabak, Takami, Rocha, and Cajueiro, 2011; Battiston, Gatti, Gallegati, Greenwald, and Stiglitz, 2012a; Battiston, Gatti, Gallegati, Greenwald, and Stiglitz, 2012b; Amini, Cont, and Minca, 2012; Elliott, Golub and Jackson, 2013; Acemoglu, Osdaglar and Tahbaz-Salehi, 2013), networks are built according to different topologies (random, small world, or scale-free), and the propagation of defaults is studied on them. The conclusions are that small world or scale-free networks are, in general, more robust to cascades (the propagation of shocks) than random networks, but they are also more prone to propagations of crises if the most central nodes (usually, the ones with more connections) are not themselves backed by sufficient funds.

Most empirical works (Boss, Elsinger, Summer, and Thurner, 2004; Müller, 2006; Soramäki, Bech, Arnold, Glass, and Beyeler, 2007; Hattori and Suda, 2008; Iori, Masi, Precup, Gabbi, and Caldarelli, 2008; Markose, Giansante, Gatkowski, and Shaghaghi, 2010; Kubelec and Sá, 2010; Minoiu and Reyes, 2011; Lee, Yang, Kim, Lee, Goh, and Kim, 2011; Upper, 2011; Battiston, Puliga, Kaushik, Tasca, and Caldarelli, 2012; Martínez-Jaramillo, Alexandrova-Kabadjova, Bravo-Benítez, and Solórzano-Margain, 2012; Hale, 2012; Kaushik and Battiston, 2012; Chinazzi, Fagiolo, Reyes, and Schiavo, 2013; Memmel and Sachs, 2013) are also based on the structure derived from the borrowing and lending between banks, and they show that those networks exhibit a core-periphery structure, with few banks occupying central, more connected positions, and others populating a less connected neighborhood. Those articles showed that this structure may also lead to cascades if the core banks are not sufficiently resistant, and that the network structures changed considerably after the crisis of 2008, with a reduction on the number of connected banks and a more robust topology against the propagation of shocks.

Section 2 of this article explains the data used. Section 3 uses the correlations between stocks in order to study the similarity of behavior in our data set. Section 4 explains Transfer Entropy and uses it in order to study the exchange of information between stocks. Section 5 builds two networks, one based on correlations, and another built on TE, and makes a study of the centrality of stocks according to complex networks theory. Section 6 studies the dynamics of both networks through times of crises, Section 7 makes simulations with shocks originating both in one particular stock and shocks exogenous to the system which affect all stocks or some sector of the economy, and Section 8 presents some conclusions.

2 Data

We work with the stocks belonging to the index S&P 500 of the New York Stock Exchange (500 stocks in the index) and the Nasdaq 100 index of Nasdaq stock exchange (100 stocks in the index). Only the stocks with a certain liquidity were considered, what means they were negotiated in nearly all the days (more than 80%) the stock exchanges operated, what eliminates a small number of stocks. There is a large intersection of stocks that are negotiated in both stock exchanges, and we eliminated any duplicate data from our sample, ending with 464 stocks. The stocks were ordered according to a sector classification used by Bloomberg, where the data was taken from. The sectors are Basic Materials (26 stocks), Energy (37 stocks), Industrial (76 stocks), Consumer, Cyclical (62 stocks), Diversified (1 stock), Financial (71 stocks), Communications (34 stocks), Technology (54 stocks), Utilities (29 stocks), and Consumer, Non-Cyclical (94 stocks).

The sectors and industries are organized in Table 1. The order of sectors is such that the most correlated

sectors are close together. The company name, tickers, sector, industry, and sub-industry of each of the stocks in the data are detailed in Appendix A. Since there is just one company in the Diversified sector, a holding company that invests in a variety of sectors, we are placing it together with the Financial sector when producing graphs or calculating aggregate data, for visual purposes.

Sector	Industries
Basic Materials	Chemicals, Forest Products and Paper, Iron/Steel, Mining, Quarrying.
Energy	Coal, Oil & Gas, Oil & Gas Services, Pipelines.
Industrial	Aerospace/Defense, Building Materials, Electrical Components & Equipment, Electronics, Engineering & Construction, Hand/Machine Tools, Machinery-Construction & Mining, Machinery-Diversified, Metal Fabricate/Hardware, Miscellaneous Manufacturing, Packaging & Containers, Transportation.
Consumer, Cyclical	Airlines, Apparel, Automanufacturing, Autoparts & Equipment, Distribution/Wholesale, Entertainment, Home Builders, Home Furnishing, Houseware, Leisure Time, Lodging, Retail, Textiles, Toys/Games/Hobbies.
Diversified	Holding Companies-Diversified.
Financial	Banks, Diversified Financial Services, Insurance, REITS, Savings & Loans.
Communications	Advertising, Internet, Media, Telecommunications.
Technology	Computers, Electronic Components & Equipment, Electronics, Office/Business Equipment, Semiconductors, Software.
Utilities	Electric, Gas.
Consumer, Non-Cyclical	Agriculture, Beverages, Biotechnology, Commercial Services, Cosmetics/Personal Care, Food, Healthcare Products, Healthcare Services, Household Products/Wares, Pharmaceuticals.

Table 1. Sectors and industries as classified by Bloomberg.

The daily closing prices of each stock are used in order to calculate log-returns, given by

$$R_t = \ln(P_t) - \ln(P_{t-1}) , \quad (1)$$

where P_t is the closing price of the stock at day t and P_{t-1} is the closing price of the same stock at day $t - 1$. We worked with the log-returns in order to avoid issues due to the nonstationarity of the time series of the closing prices. Working with end of trading day returns, we are not studying the high frequency trading of the market, that drives prices during the day, but the slower dynamics of prices along longer periods. We will do some work with intraday data in the near future.

3 Correlations

Our first analysis of the data is based on the familiar correlation structure between the stocks in our sample. We use the Pearson correlation, which is given by

$$C_{ij} = \frac{\sum_{k=1}^n (x_{ik} - \bar{x}_i)(x_{jk} - \bar{x}_j)}{\sqrt{\sum_{k=1}^n (x_{ik} - \bar{x}_i)^2} \sqrt{\sum_{k=1}^n (x_{jk} - \bar{x}_j)^2}} , \quad (2)$$

where x_{ik} is element k of the time series of variable x_i and x_{jk} is element k of the time series of variable x_j , and \bar{x}_i and \bar{x}_j are the averages of both time series, respectively.

The Pearson correlation is used in order to calculate the linear correlation between variables. Other types of correlation measures, like the Spearman rank correlation and the Kendall tau rank correlation, are used in order to calculate nonlinear relations between variables. Here, we apply the usual Pearson correlation because it has been shown (Sandoval, 2013) that the results using this correlation measure are very similar to the Spearman rank correlation for the financial data we are using and is much faster to compute.

The structure of the resulting correlation matrix may be visualized in Figure 1 (left, where on the right the same picture is plotted with the sectors highlighted), where we plot a heat map of the elements of the correlation

matrix, with lighter colors denoting higher correlations and darker colors denoting lower correlations. The figure displays the correlations in such a way that the leftmost and lowest corner corresponds to the correlation between element 1 with itself. The number of each stock grows from left to right and from the bottom to the top. The same configuration will be used in all other representations of matrices in this article. As expected, the diagonal elements are the brightest ones, with correlation 1 between all stocks and themselves. It is also possible to identify some clusters, related with sector and industry of stocks.

One can notice some black or dark lines, corresponding to stocks that do not correlate well with other stocks in the sample. For Basic Materials, there are clusters and subclusters, corresponding to industries; Energy is a large, compact cluster; Industrial has many subclusters based on industries, but all of them very sparse; inside Consumer, Cyclical, there are some sparse clusters and a compact one in Distribution/Wholesale; Financial has a sparse subcluster for Banks and a compact subcluster for REITS; for Communications, there is an inner cluster corresponding to the industry Media; Technology has a subcluster of the Semiconductors industry; Utilities form a compact cluster; and for Consumer, Non-Cyclical, there is a sparse subcluster for the industry Health Care Services and two very sparse ones for Healthcare Products and for Pharmaceuticls.

Values in Figure 1 go from -0.0429 (slightly anticorrelated) to 1 (totally correlated), with a maximum of 0.9064 if we exclude the self-correlations (which are always equal to 1). We may compare these values with the ones that may be obtained by considering all time series of data, but randomly shuffling each time series independently, so that any true correlation between the time series is broken, but the probability distribution of each one is maintained. By computing 1,000 simulations randomizing the time series and then calculating the correlation matrix for each simulation leads to a minimum correlation -0.10 ± 0.01 (average \pm standard deviation) and a maximum correlation 0.10 ± 0.02 (excluding self-correlations). Figure 2 shows a histogram of the correlation matrix values and a histogram obtained from the simulations with randomized data, both with the autocorrelations removed. It is clearly visible that, except for a small quantity of classes, the correlation matrix for real data presents very distinct results from the correlations obtained with randomized data. So, the correlation between stocks is well above the correlation predicted for uncorrelated data.

4 Transfer Entropy

Although useful for determining which stocks behave similarly to others, the correlations between them cannot establish a relation of causality or of influence, since the action of a stock on another is not necessarily symmetric. A measure that has been used in a variety of fields, and which is both dynamic and non-symmetric, is *Transfer Entropy*, developed by Schreiber (2000), which is based on the concept of *Shannon Entropy*, first developed in the theory of information by Shannon (1948). Transfer entropy has been used in the study of cellular automata in Computer Science, in the study of the neural cortex of the brain, in the study of social networks, in Statistics, and also in the analysis of financial markets, as in the works of Marschinski and Kantz (2002), Baek, Jung, and Moon (2005), Kwon and Yang (2008a), Kwon and Yang (2008b), Jizba, Kleinert, and Shefaat (2012), Peter, Dimpfl, and Huergo (2012), Dimpfl and Peter (2012), Kim, An, Kwon, and Yoon (2013), Li, Liang, Zhu, Sun, and Wu (2013), Dimpfl and Peter (2014), and Sandoval (2014). In this section, we shall describe the concept of Transfer Entropy (TE), using it to analyze the data concerning the 464 stocks in our sample and their lagged counterparts.

When one deals with variables that interact with one another, then the time series of one variable Y may influence the time series of another variable X in a future time. We may assume that the time series of X is a Markov process of degree k , what means that a state i_{n+1} of X depends on the k previous states of the same variable. This may be made more mathematically rigorous by defining that the time series of X is a Markov state of degree k if

$$p(i_{n+1}|i_n, i_{n-1}, \dots, i_0) = p(i_{n+1}|i_n, i_{n-1}, \dots, i_{n-k+1}) , \quad (3)$$

where $p(A|B)$ is the conditional probability of A given B , defined as

$$p(A|B) = \frac{p(A, B)}{p(B)} . \quad (4)$$

What expression (3) means is that the conditional probability of state i_{n+1} of variable X on all its previous

states is the same as the conditional probability of i_{n+1} on its k previous states, meaning that it does not depend on states previous to the k th previous states of the same variable.

One may assume that state i_{n+1} of variable X also depends on the ℓ previous states of variable Y . The concept is represented in Figure 3, where the time series of a variable X , with states i_n , and the time series of a variable Y , with states j_n , are identified.

We may now define the concept of TE from a time series Y to a times series X as the average information contained in the source Y about the next state of the destination X that was not already contained in the destination's past. We assume that element i_{n+1} of the time series of variable X is influenced by the k previous states of the same variable and by the ℓ previous states of variable Y . The values of k and ℓ may vary, according to the data that is being used, and to the way one wishes to analyze the transfer of entropy of one variable to the other.

Transfer Entropy from variable Y to variable X is defined as

$$\begin{aligned} TE_{Y \rightarrow X}(k, \ell) &= \sum_{i_{n+1}, i_n^{(k)}, j_n^{(\ell)}} p(i_{n+1}, i_n^{(k)}, j_n^{(\ell)}) \log_2 p(i_{n+1} | i_n^{(k)}, j_n^{(\ell)}) \\ &\quad - \sum_{i_{n+1}, i_n^{(k)}, j_n^{(\ell)}} p(i_{n+1}, i_n^{(k)}, j_n^{(\ell)}) \log_2 p(i_{n+1} | i_n^{(k)}) \\ &= \sum_{i_{n+1}, i_n^{(k)}, j_n^{(\ell)}} p(i_{n+1}, i_n^{(k)}, j_n^{(\ell)}) \log_2 \frac{p(i_{n+1} | i_n^{(k)}, j_n^{(\ell)})}{p(i_{n+1} | i_n^{(k)})}, \end{aligned} \quad (5)$$

where i_n is element n of the time series of variable X and j_n is element n of the time series of variable Y , $p(A, B)$ is the joint probability of A and B , and

$$p(i_{n+1}, i_n^{(k)}, j_n^{(\ell)}) = p(i_{n+1}, i_n, \dots, i_{n-k+1}, j_n, \dots, j_{n-\ell+1}) \quad (6)$$

is the joint probability distribution of state i_{n+1} , of state i_n and its k predecessors, and the ℓ predecessors of state j_n , as in Figure 3.

This definition of TE assumes that events on a certain day may be influenced by events of k and ℓ previous days. Since most empirical data on financial markets suggest that log-returns of the prices of stocks have low memory (what is not true for volatility), we shall assume that we have a Markov state of degree 1 with respect to variables X and Y , what means that we will consider that only the previous day in the time series of X and Y contain some information on the time series of X at some target day. By doing so, formula (5) for the TE of Y to X becomes simpler:

$$TE_{Y \rightarrow X} = \sum_{i_{n+1}, i_n, j_n} p(i_{n+1}, i_n, j_n) \log_2 \frac{p(i_{n+1} | i_n, j_n)}{p(i_{n+1} | i_n)} = \sum_{i_{n+1}, i_n, j_n} p(i_{n+1}, i_n, j_n) \log_2 \frac{p(i_{n+1}, i_n, j_n) p(i_n)}{p(i_{n+1}, i_n) p(i_n, j_n)}, \quad (7)$$

where we took $k = \ell = 1$, meaning we are using lagged time series of one day, only.

Applying (7) to our sample of data, one obtains a TE matrix, depicted in Figure 4, on the left, and with the sectors highlighted, on the right. The figure represents the TE going from elements of the vertical axis to elements of the horizontal axis, from lines to columns. The first feature that may be observed is that, although TE is not symmetric, the TE matrix shown in Figure 4 is remarkably symmetric, although not completely so. The values of TE go from 0 (darker colors) to 0.4067 (brighter colors).

Since brighter colors imply larger TE and darker colors imply lower TE, one can notice regions of low TE being received by stocks of the Utilities sector (horizontal lines from 341 to 370), and also from this same sector to all others (vertical lines from 341 to 370). There is also little TE from stocks inside the Utilities sector. Comparing with Figure 1, we may see that the Utilities sector is very correlated within itself, but little correlated with other sectors. We also see low TE from the Basic Materials sector, particularly from the Chemicals industry, to all others, and also from the Oil Companies industry in the Energy sector, from the Aerospace/Defense industry in the Industrial sector, part of the Retail industry of the Consumer, Cyclical

sector, and from many industries of the Consumer, Non-Cyclical sector, with similar results for the stocks that receive little TE from the others.

Another feature are the larger values of TE between stocks of the Financial sector with themselves and with stocks of the other sectors. This indicates an exchange of information going both from the time series of stocks belonging to the Financial sector to the other stocks and from all stocks to the ones of the Financial sector. There is slightly less TE flowing from REITS to other REITS, what is typical of time series that behave as a block (very highly correlated, as can be seen from Figure 1), and thus do not exchange much information among themselves. The same explanation may be given to the lack of TE between stocks of the Utilities sector and themselves. There is also a good amount of TE from stocks belonging to the Communications and Technology sectors to other sectors and to themselves, and isolated lines of TE from stocks of the Basic Materials sector (Mining industry) and of the Consumer, Cyclical sector (Home Builders industry).

The size of the bins used in the calculations of the probabilities in (7) changes the resulting Transfer Entropy (TE) values. In Figure 4, we use a binning size 0.02, what leads to a much larger number of bins and to a much longer calculation time, but also gives a better resolution, given the amount of data used (see Sandoval, 2014b, for a better discussion of the information of the binning size on TE).

Although useful, the picture obtained from the TE matrix is not very informative, as there is little TE from one stock to another in the same day if we use daily returns. One different approach, applied to stocks of the financial sector in many stock exchanges around the world (Sandoval, 2014b) and to stock market indices (Sandoval and Kenett, 2014), is to consider the lagged time series of all stocks, together with the original time series, in order to build a larger set of data, twice the size of the original one, where original and lagged stocks are considered as different variables. This approach was first developed by Sandoval (2014a) in order to study stock markets around the world, which do not operate at the same times, using correlation. When applied to TE, one obtains very interesting results, shown in Figure 5, which displays the TE from all stocks to all stocks, original and lagged, with original stocks represented first, and lagged stocks represented next. The resulting expanded TE matrix is clearly not symmetric, and it may be divided into four sectors. The first sector (Sector 11), the lower left corner of the TE matrix, represents the TE from original to original stocks, and is the same as the TE represented in Figure 4. Now the second sector (Sector 21), top left corner of the TE matrix, represents the TE from lagged variables to the original ones. This sector presents some interesting structure, with brighter colors indicating large values of TE from the time series of stocks on the day before to the time series of stocks of the next day. There is a bright diagonal line inside this sector, which is the TE from one stock to itself on the next day, what is to be expected from the definition used (7), and other bright regions representing the exchange of information between time series of consecutive days. The third sector (Sector 12), lower right corner, represents the TE from original to lagged indices, and it is mostly noise, what is to be expected, since the transfer of information from the future to the past is not physically possible. The last sector (Sector 22), top right corner, shows the TE from lagged to lagged variables, and is mostly similar to Sector 11.

Figure 6 offers a closer look at Sector 21, representing the TE from lagged variables to original ones. Here also, one may see that, although Transfer Entropy is an asymmetric measure, the graph is particularly symmetric. Now, one must have in mind that this is the Transfer Entropy from lagged data to original (unlagged) variables, so this is a part of the very asymmetric expanded TE matrix in Figure 5 which is rather symmetric itself. The values go from 0.0440 to 2.8029, about seven times larger than the maximum TE for sector 11.

There is a remarkable resemblance between the TE from lagged to original variables and the correlation matrix obtained before (Figure 1). This may be the effect of TE from one day to the other leading to the uniformity of behavior of stocks on the next day. Again, one may see strong values of TE from stocks of the Mining and Quarrying industries of the Basic Materials sector to themselves, from stocks of the Energy sector to themselves, from stocks of the Banks and REITS industries of the Financial sector to themselves, and from stocks of the Semiconductors industry of the Technology sector to themselves.

The similarity between the TE matrix for Sector 21 and the correlation matrix is striking. Figure 7 shows the scatter plot between both measures, and one can notice a nonlinear relation between them. The dots forming a vertical line at the right of the figure are due to the autocorrelations and to the TE from lagged variables to their original counterparts. The Pearson correlation coefficient of both measures is 0.6030, the

Spearman rank correlation is 0.5690, and the Kendall tau rank correlation is 0.4037. These correlations are quite similar when the main diagonals of both matrices are removed. Besides the terms of autocorrelation and transfer entropy from one variable to itself on the next day, there are two groups that may be identified. The first one is for correlations close to zero, which are correlated with TE values that are either small or medium; the second one seems to be a relation between correlation and the square of TE.

This similarity between both measures indicate that the information sent from one stock to another stock on the next day and vice-versa is followed by a similar behavior of both stocks on this next day. So, the exchange of information between stocks seems to lead to a larger correlation between them on the next day.

Analyzing now the internal structures of the TE matrices for sectors 11 and 21, and comparing them with TE matrices obtained from randomized data, we may obtain an interval of validity of our results if compared with results of unrelated data. We made 10 simulations by flushing the data in each time series randomly, so as to destroy any relations between time series but maintain each probability distribution. We used just ten simulations because of the long computational times necessary to perform them, and also because there is very little difference between one simulation and another. Comparing the probability distributions of real data and of the randomized data, we obtain the probability distributions in Figure 8, where the left graph shows the results for sector 11 and the right graph displays results for sector 21.

Most of the values for sector 11 of the TE expanded matrix fall into the possible values for randomized data, so that most results may be seen as probably resulting from pure statistical noise, but results for sector 21 clearly detach themselves from results obtained from randomized data, indicating that there is a substantial amount of information that could not possibly be generated by statistical noise.

5 Network structure

Now we will build a network structure for the stocks based on their correlation matrix. This will be done by representing each stock in our sample as a node and correlations between them as edges. One way to do that is to represent the nodes in an abstract space where the distances between them are associated with their correlations: stocks that are more correlated appear as nodes that are closer together, and stocks that are less correlated appear as nodes that are farther apart from each other.

There are many ways to define a distance measure based on a correlation matrix, but the most used one in applications to financial markets is given by Mantegna (1999):

$$d_{ij} = \sqrt{2(1 - C_{ij})} , \quad (8)$$

where C_{ij} is the correlation between nodes i and j . As correlations between stocks vary from -1 (anticorrelated) to 1 (completely correlated), the distances between them vary from 0 (totally correlated) to 2 (completely anticorrelated). Totally uncorrelated stocks would have distance 1 between them.

Based on the distance measures, m -dimensional coordinates are assigned to each stock using an algorithm called Classical Multidimensional Scaling (Borg and Groener, 2005), which is based on minimizing the stress function

$$S = \left[\frac{\sum_{i=1}^n \sum_{j>i}^n (\delta_{ij} - \bar{d}_{ij})^2}{\sum_{i=1}^n \sum_{j>i}^n d_{ij}^2} \right]^{1/2} , \quad \bar{d}_{ij} = \left[\sum_{a=1}^m (x_{ia} - x_{ja})^2 \right]^{1/2} . \quad (9)$$

where δ_{ij} is 1 for $i = j$ and zero otherwise, n is the number of rows of the correlation matrix, and \bar{d}_{ij} is an m -dimensional Euclidean distance (which may be another type of distance for other types of multidimensional scaling). The outputs of this optimization problem are the coordinates x_{ia} of each of the nodes, where $i = 1, \dots, n$ is the number of nodes and $a = 1, \dots, m$ is the number of dimensions in an m -dimensional space. The true distances are only perfectly representable in m dimensions, but it is possible for a network to be well represented in smaller dimensions. In the case of this article we shall consider $m = 2$ for a 2-dimensional visualization of the network, being the choice a compromise between fidelity to the original distances and the easiness of representing the networks in a two dimensional medium.

Figure 9 shows the stocks represented as nodes, with legends identifying different sectors. There is a crowded center where the majority of nodes of Communications and Technology stocks concentrate. Also occupying part of the center and its neighborhood are the stocks of Consumer, Cyclical, Consumer, Non-Cyclical, Financial, and Industrial sectors. The stocks belonging to Basic Materials are spread around the Industrial and Energy sectors; the Energy and Utilities sectors are set clearly apart from the other sectors, and the one stock belonging to the Diversified sector is also apart from the other stocks.

Figure 9 shows only the nodes of the network built using correlation, since drawing connections among all nodes would make the figure very confusing, since each node is connected to all others. There are filtering methods that drastically reduce the number of connections, and one of them, asset graphs, will be discussed in Subsection 5.4.

For Transfer Entropy, we may again try to produce a map of the nodes according to distances between stocks. The problem now is that distance is a symmetric measure, and Transfer Entropy is not. Another problem is that TE is not normalized. We may correct the latter problem by defining a normalized version of TE by dividing each column by the value of the TE from the lagged variable to itself. So, the TE from one lagged variable to itself is, at maximum, 1. One must be aware that this is not the measure usually called *Normalized Transfer Entropy* in the literature, which is calculated in a very different way, and is not used here.

By using the definition given by (8), we may calculate a matrix for which the main diagonal is zero, but this matrix is still not symmetric, as a distance matrix must be. We chose to symmetrize the matrix by setting $d_{ij} = d_{ji}$ if $d_{ij} > d_{ji}$ and $d_{ji} = d_{ij}$, otherwise, what means that we always consider the smallest between the two values d_{ij} and d_{ji} to be the distance between i and j . The resulting distance matrix is then used, applying (9), in order to calculate a set of coordinates for each stock as a node in a space where distances are similar to the ones given by the symmetrized distance matrix.

Figure 10 shows the two dimensional figure that results from this procedure, where stocks are represented as nodes colored according to sector, which is very similar to the graph obtained from correlations. The distances between nodes in the graph represent the best approximation to the distances calculated using the distance matrix based on Transfer Entropy.

Other choices for normalization or symmetrizing would lead to different graphs, but only slightly different. From Figure 10, one may see a detachment of the stocks belonging to the Energy, Financial, and Utilities industries. The other stocks seem to concentrate in a large cluster, although they maintain some coherence inside that cluster.

5.1 Node Strength

The correlation and Transfer Entropy networks produced by the correlation matrix of stocks and the TE between lagged and original stocks are *weighted networks*, what means that the edges between nodes (stocks) have values attached to them, which are the correlations or the TE relations between stocks. For such networks, the main measure of the centrality of a node (in many ways, of its importance in the network) is *Node Strength* (NS) (Newman, 2010), which for an undirected network such as the one obtained through correlation is the sum of all weights of the edges of a node (stock) with other nodes (stocks),

$$NS_i = \sum_{j=1}^N C_{ij} , \quad (10)$$

where C_{ij} is element (i, j) of the correlation matrix, and N is the number of stocks in our sample (464 stocks).

Since Transfer Entropy is asymmetric, there is a difference between the Transfer Entropy from one stock to all others and the Transfer Entropy from all stocks to one stock, so that the network formed using TE is a directed one. For directed networks, Node Strength assumes two guises: In Node Strength (NS_{in}), which is the sum of the weights of all edges that go from all nodes to a particular node, and Out Node Strength (NS_{out}), which is the sum of the weights of a node to all other nodes (Newman, 2010),

$$NS_{in}^i = \sum_{j=1}^N TE_{ij} , \quad NS_{out}^j = \sum_{i=1}^N TE_{ij} . \quad (11)$$

Table 2 shows the values of the Node Strength for the network based on correlations for the ten stocks with highest centrality values. The stocks of Financial and Chemical companies occupy the first places, what means that those stocks have a behavior more similar to other stocks. Stocks of the Industrial sector and one stock of the Consumer, Cyclical sector follow.

Node Strength	Company	Sector	Industry
242.52	Franklin Resources Inc	Financial	Diversified Financial Services
241.31	T. Rowe Price Group Inc	Financial	Diversified Financial Services
239.54	DoubleDragon Properties Corp	Basic Materials	Chemicals
239.14	PPG Industries Inc	Basic Materials	Chemicals
235.54	Emerson Electric Co	Industrial	Electrical Components & Equipment
234.84	Sigma-Aldrich Corp	Basic Materials	Chemicals
234.15	PACCAR Inc	Consumer, Cyclical	Auto Manufacturers
232.87	Loews Corp	Financial	Insurance
232.82	Dover Corp	Industrial	Miscellaneous Manufacturing
232.78	United Technologies Corp	Industrial	Aerospace / Defense

Table 2. Classification of stocks with highest Node Strength, their sector and industry classifications. Only the ten stocks with highest centrality values are shown.

Table 3 represents the centrality results for the network based on TE, showing the top 10 stocks according to in or out Node Strength. All top 10 companies whose stocks receive the most information from all other stocks belong to the Financial sector, and mainly to the Insurance industry, what is understandable, since the prices of stocks belonging to insurance companies are highly influenced by the prices of companies they ensure. Now the companies whose stocks send the most information to all other stocks are more diverse, with two stocks of companies that belong to the Financial sector occupying the two top positions. Most stocks of the Financial sector are both major senders and major receivers of information.

In Node Strength	Company	Sector	Industry
269.38	Lincoln National Corp	Financial	Insurance
267.27	Hartford Financial Services Group Inc/The	Financial	Insurance
262.53	Huntington Bancshares Inc/OH	Financial	Banks
259.25	Principal Financial Group Inc	Financial	Insurance
254.91	American International Group Inc	Financial	Insurance
254.70	Regions Financial Corp	Financial	Banks
253.71	E*TRADE Financial Corp	Financial	Diversified Financial Services
251.81	Prudential Financial Inc	Financial	Insurance
250.69	Fifth Third Bancorp	Financial	Banks
249.77	Citigroup Inc	Financial	Banks
Out Node Strength	Company	Industry	Sub Industry
288.90	E*TRADE Financial Corp	Financial	Diversified Financial Services
276.41	Lincoln National Corp	Financial	Insurance
275.20	Lennar Corp	Consumer, Cyclical	Home Builders
274.94	Cliffs Natural Resources Inc	Basic Materials	Iron / Steel
274.57	Huntington Bancshares Inc/OH	Financial	Banks
273.39	American International Group Inc	Financial	Insurance
272.25	Allegheny Technologies Inc	Basic Materials	Iron / Steel
271.55	Sirius XM Holdings Inc	Communications	Media
269.63	Hartford Financial Services Group Inc/The	Financial	Insurance
269.44	Regions Financial Corp	Financial	Banks

Table 3. Classification of stocks with highest Node Strength, their sector and industry classifications. Only the ten stocks with highest centrality values are shown.

5.2 Aggregate Data

In order to understand how sectors relate to one another, we made use of aggregate data, which resulted in correlations and TE relations between sectors. The aggregate data was constructed in the following way: first, we calculated the correlations between stocks belonging to the same sector, and then constructed a correlation matrix for each sector. From those correlation matrices, we calculated eigenvalues and eigenvectors for each correlation matrix, with each eigenvector being a vector associated to one of the scalar eigenvalues. For each of them, one eigenvalue detaches from all others, being much larger than most of them, what was first seen in stock markets in the work of Laloux, Cizeau, Bouchaud, and Potters (1999), and verified by a number of other

works since then for many types of markets (for a comprehensive bibliography on the subject, see Sandoval and Franca, 2012).

Each eigenvalue may be seen as an indicator of the level of risk of a portfolio built with the stocks (or indices) of the correlation matrix by using the elements of the eigenvector associated with it as weights for each stock in the portfolio. So, the highest eigenvalue expresses the risk of a portfolio with the maximum risk, and associated to this eigenvalue is an eigenvector that is remarkably homogeneous in terms of the weights given to each element of this portfolio. This largest eigenvalue is then associated with the systemic risk of the market, being the corresponding eigenvector associated with a *market mode*.

The agreement of an index built using as weights the elements of the eigenvector corresponding to the largest eigenvalue of the correlation matrix of stocks of a certain stock market, when compared to that stock market index, as an example, is nearly perfect. So, we may use this eigenvector in order to build an index for each sector, and then use all indices thus obtained in order to calculate a correlation matrix and a TE matrix. The results are plotted in Figure 11. Both graphs reveal similar information, indicating again a relation between the transfer of information of a sector from one day before to the next day of another sector and the correlation of both in the next day. There is a lot of interaction between the Basic Materials sector and the Industrial Sector, and the Energy sector doesn't seem to interact much with the others, except for a light interaction with the Basic Materials sector. The Industrial sector interacts strongly with the Consumer, Cyclical, Financial, Communications and Technology sectors, what also happens in a lesser degree with the interactions of the Financial sector. Actually, these 5 sectors form a highly interacting block, with stronger interactions between the Communications and Technology sectors. It is worthwhile remembering that the one stock belonging to the Diversified sector has been incorporated into the Financial sector.

Tables 4 and 5 show the Node Strengths, and the In and Out Node Strengths, for the correlation and the TE matrices. The most central sector according to correlation is the Industrial one, followed by Communications. The sectors with the smallest value for Node Strength are Energy and Utilities. According to TE, the Industrial sector is the main sender and receiver of information, followed by the Communications and Financial sectors. The Energy and the Utilities sectors are the ones that send and receive the least information from the other sectors, although it is worth remembering that the energy sector is very much correlated with itself and also share much information among its stocks.

Node Strength	Sector
6.80	Industrial
6.67	Communications
6.49	Consumer, Non-Cyclical
6.47	Basic Materials
6.38	Consumer, Cyclical
6.22	Technology
6.08	Financial
5.53	Energy
5.44	Utilities

Table 4. Classification of industries according to Node Strength for aggregate data on sectors.

In Node Strength	Sector	Out Node Strength	Industry
4.61	Industrial	4.62	Industrial
4.25	Communications	4.24	Financial
4.18	Financial	4.23	Communications
4.16	Basic Materials	4.17	Consumer, Cyclical
4.13	Consumer, Cyclical	4.12	Basic Materials
3.88	Technology	3.88	Technology
3.50	Consumer, Non-Cyclical	3.45	Consumer, Non-Cyclical
2.94	Energy	3.01	Energy
2.42	Utilities	2.34	Utilities

Table 5. Classification of sectors according to In and Out Node Strengths for aggregate data on sectors.

One can also see in Table 5 that there is a slight asymmetry between the In and Out Node Strengths of sectors. As an example, the Financial sector sends slightly more information than it receives, and the Communications sector receives slightly more information than it sends. It is interesting to analyze these asymmetries between sent and received information, what is done in the next section.

5.3 Asymmetries in Transfer Entropy

As we could see, although Transfer Entropy is an asymmetric measure, it is highly symmetric if we consider the Transfer Entropy from lagged variables to original ones. The differences between $T_{I \rightarrow J}$ and $T_{J \rightarrow I}$ will be called here Excess Transfer Entropy, defined in terms of sector 21 of the TE matrix as

$$\text{ExcessTE}(i, j) = \text{TESect21}(i, j) - \text{TESect21}(j, i), \quad (12)$$

where TESect21 is just sector 21 of the TE matrix. The result is an antisymmetric matrix with information on the difference between the amount of information a time series of a stock I transfer to the time series of another stock J on the next day and the amount of information that stock J transfer to stock I of the next day. For our set of data, it ranges from -0.0897 to 0.0897.

The graphs of both the ExcessTE matrix for all stocks and the ExcessTE matrix for aggregate data by sectors are drawn in Figure 12 (left graph for stocks and right graph for sectors). The first graph highlights regions of high excess TE, from some particular stocks to all others, the main region being due to lagged variables to the stocks belonging to the Utilities sector. For aggregate data (right graph), there is an Excess TE from the Energy sector to the Basic Materials, Industrial, Consumer, Cyclical, Financial, Communications, Utilities, and Consumer, Non-Cyclical sectors. There is also a strong Excess TE from Consumer, Cyclical to Basic Materials, and to the Technology, Utilities and Consumer, Non-Cyclical sectors. The Financial sector also has an Excess TE to these same sectors, with emphasis on Excess TE to the Utilities sector.

Table 6 shows the In and Out Node Strengths of the top 10 stocks that have the major imbalances between the information they send and the information they receive from all other stocks. The major Excess receivers are a major oil company and a major pharmaceutical company, followed by two energy companies, and the top excess senders are quite diverse.

In order to analyze which are the major excess sender and receiver sectors, we calculate the In and Out Node Strengths of the Excess TE data for aggregate data. The result is in Table 7, showing the positions of all sectors. The top two senders of Excess TE are the Energy and Financial sectors, and the major Excess TE receivers are the Utilities and Basic Materials sectors.

In Node Strength	Company	Sector	Industry
11.42	Exxon Mobil Corp	Energy	Oil & Gas
10.93	Johnson & Johnson	Consumer, Non-Cyclical	Pharmaceuticals
10.70	Entergy Corp	Utilities	Electric
10.65	Wisconsin Energy Corp	Utilities	Electric
10.32	Chevron Corp	Energy	Oil & Gas
10.17	American Electric Power Co Inc	Utilities	Electric
10.05	Praxair Inc	Basic Materials	Chemicals
9.92	PepsiCo Inc	Consumer, Non-Cyclical	Beverages
9.87	HJ Heinz Co	Consumer, Non-Cyclical	Food
9.87	Northeast Utilities	Utilities	Electric
Out Node Strength	Company	Sector	Industry
22.42	Sirius XM Holdings Inc	Communications	Media
22.19	Titanium Metals Corp	Basic Materials	Mining
21.93	JDS Uniphase Corp	Communications	Telecommunications
20.26	Allegheny Technologies Inc	Basic Materials	Iron / Steel
19.83	Lennar Corp	Consumer, Cyclical	Home Builders
19.24	Monster Beverage Corp	Consumer, Non-Cyclical	Beverages
19.09	Netflix Inc	Communications	Internet
18.66	Regeneron Pharmaceuticals Inc	Consumer, Non-Cyclical	Biotechnology
17.98	Advanced Micro Devices Inc	Technology	Semiconductors
17.43	NVIDIA Corp	Technology	Semiconductors

Table 6. Classification of stocks with highest In and Out Node Strengths, based on Excess TE, their sector and industry classifications. Only the ten stocks with highest centrality values are shown.

In Excess Node Strength	Sector	Out Excess Node Strength	Sector
0.063	Energy	0.077	Utilities
0.060	Financial	0.043	Basic Materials
0.045	Consumer, Cyclical	0.042	Consumer, Non-Cyclical
0.014	Industrial	0.025	Communications
0.004	Technology		

Table 7. Classification of stocks with highest In and Out Node Strengths, based on Excess TE, for aggregate data by sectors. Negative values have not been represented.

5.4 Asset Graphs

As mentioned before, there are many ways to filter the large amount of information provided by the correlation and the TE matrices. One way to do so is to use *asset graphs*, which are networks built by establishing a threshold value above or below which all interactions are not considered, leaving fewer connections and nodes. Asset graphs have been used in a variety of works in finance, like in Onela, Chakraborti, Kaski, and Kertész (2002), (2003), (2004), Onela, Chakraborti, Kaski, and Kertész, and Kanto (2003), Onnela, Chakraborti, and Kaski (2003), Sinha and Pan (2003), Ausloos and Lambiotte (2007), and Sandoval (2012).

In our particular case, we shall use threshold values for the correlation matrix and for the TE matrix below which edges between the nodes (stocks) are not considered, and all nodes not connected to any other node are also deleted. We used as examples threshold values that made it possible to distinguish between many clusters, a compromise between having too many connections or too few of them. For correlation, we used a threshold value 0.8. So, a new matrix was built on the correlation matrix, where all elements of the matrix for which the corresponding element in the correlation matrix was below the threshold was set to zero and all elements above it were set to one, what is called an *adjacency matrix*. Then, all nodes without any connection were removed, resulting in a network of fewer nodes and fewer edges. The result is plotted in Figure 13, where one can see 13 clusters, some of them as small as two nodes and the largest of them, corresponding to REITS, with 14 nodes. The sectors and industries that make up the clusters are specified in the same figure, with large networks of Oil & Gas companies and also of Banks. Stocks are represented by their tickers, as in Appendix A.

An asset graph based on TE with threshold value 0.7 is built and is shown in Figure 14. The clusters formed are similar to the clusters obtained from correlation, but now the cluster of REITS is smaller, the cluster of banks is larger, and there is just one large cluster of Oil & Gas companies. There is also a cluster of Insurance companies now. In this network, single directed links are represented with arrows, and links that occur in both directions are represented as lines without arrows.

6 Dynamics

The use of data for the production of static measurements of the relations between stocks offer some information about them, but the dynamics of those relations reveal how they evolve in time and how they react to external phenomena and to consequences of their own interactions. In this section, we study the dynamics of the correlations and of the exchange of information of the time series of stocks as measured by the Pearson correlation and Transfer Entropy, respectively. We start by considering snapshots by semester, and then use running windows in order to study the development of the relations between stocks as measured by correlation and by Transfer Entropy.

The correlations between stocks change in time, becoming larger in times of crisis. Figure 15 shows correlation matrices calculated using data semester by semester, from 2003 to 2012. It is easy to notice the much brighter colors in the second semester of 2008 (the height of the US Subprime Crisis) and in the second semester of 2011 (the height of the European Sovereign Debt Crisis). The average correlation in 2011 was even higher than in the crisis of 2008, thus showing that during part of the European Sovereign Debt Crisis the stocks of the US market behaved essentially in the same way. Looking at sectors, the Energy sector is very connected in itself, but not very connected to others, particularly prior to 2008. Some similar behavior can be seen for the Utilities sector, during some periods of time before and after 2008.

In a recent work, Buccheri, Marmi, and Mantegna (2013) also studied the correlations within the US stock market, but using industrial indices on a larger span of time than ours, with comparable results when within the same time span we use.

In Figure 16, we analyze the evolution of TE from lagged to original variables in time, using windows comprising data from each semester from 2003 to 2012. For the calculations in Figure 16, we used a binning of size 0.1, since it is more appropriate due to the small sample for each semester and also faster to calculate. One may see a rise in Transfer Entropy during periods of crisis, like at the 2008 Subprime Crisis and the 2011

European Sovereign Debt Crisis, very much like the rise of correlation in periods of crisis. Just prior to the crisis of 2008, we can detect a rise in the TE between stocks of the REITS industry in the Financial sector, in the Communications sector, and in the Technology sector.

For a more continuous analysis of the evolution of correlation and TE along the years, we considered running windows of 100 days of data each, shifting by one day at a time. For each correlation matrix calculated, we calculated the average of the node strengths of all stocks; for each TE matrix, we calculated the average in and out node strengths of all stocks. Then, by dividing these node strengths by the number of stocks, $N = 464$, we obtained what we call the Mean Correlation (average of the node strengths divided by N), and the Mean In and Out Transfer Entropy (respectively, the in and out node strengths, divided by N). In Figure 17, we plot the mean volatility of stocks (as given by the absolute values of their log-returns) together with the mean correlation (calculated from the correlation matrices) and the mean in and out transfer entropy (calculated from the TE matrices). Since the results for correlation and TE are based on windows of 100 days of data, we plot each result at the last day of the window, so that we never consider effects that are in the future of the day to which the result is associated. As a consequence, all averages on node strengths appear as zero in the first 100 days, what does not happen for the mean volatility.

Looking at Figure 17, the mean correlation is large for the periods of crisis, at the end of 2008, at the beginning of 2010, and at the end of 2011. Note that the mean correlation between stocks is larger for the period related with the height of the European Sovereign Debt Crisis than it was during the 2008 Subprime Crisis. The mean in and out TEs are almost indistinguishable from each other, and both have the same behavior as the mean correlation between stocks: there is a rise in mean Transfer Entropy in times of crisis. There are, though, some important differences. The first one is that the mean TE in and the mean TE out both present lower results to the crisis in 2010 than the results obtained with correlation, following more closely the rises and falls of the volatility. Now the mean correlation rises with the crisis of 2008, but then remains high for the remaining time. So, although there hasn't been a steady rise in the exchange of information between stocks, there seems to be a steady rise in the correlation between them.

We may wish to analyze the behavior of stocks separately. This is done by considering the node strength of each stock and their in and out node strengths. In Figure 18, we plot the volatility of each stock in the sample in time, calculated as the absolute value of its log-return, the mean correlation, given by the stock's node strength in the correlation matrix, and the mean in and out TE, given by the stock's in and out node strengths, respectively.

In Figure 18, the vertical lines represent the stocks in the sample (464 of them), with the numbers delimiting each sector, and the horizontal lines represent time, as measured in years. The result of each window of 100 days is associated with the last day of the window, so the measures based on moving windows begin to appear on the 100th day of each graph, except for volatility. Note that, due to the use of windows of 100 days in the calculations of the mean correlation and the mean in and out TEs, their images appear smeared when compared with the image for volatility.

Analyzing the volatility graph, one can see three different episodes of crisis in the 10 years spanned by the data. The main one occurs at the end of 2008, and corresponds to the 2008 Subprime Mortgage Crisis of the USA. It follows two smaller periods of high volatility at the beginning of 2008, and the crisis at the end of the year starts in the Financial sector, rapidly propagating to all the other sectors. The crisis subsides only at the end of 2009, and does not affect much the Utilities sector, and slightly less the Consumer, Non-Cyclic sector. The second crisis hits, not with the same strength of the 2008 crisis, by the middle of 2010. At the time, the first signs of real instability of the Eurozone became clear when the Greek government showed no signs of being able to pay the interest on their foreign debt. By the end of 2011, the third wave of high volatility hits, stronger than the one in 2010, but still weaker than the one of 2008, when the crisis had spread to other countries of the Eurozone and there were questions about the efficacy of the policies determined by the major economic players in Europe.

Looking at the plot of the mean correlation, we can see that all stocks behave similarly in time, increasing their mean correlation with the market in times of crisis. One exception can be seen for the stocks of the Energy sector, which exhibit very low mean correlations just prior to the 2008 US Subprime Crisis (dark spot in the middle of the graph), what may be associated with the 2000s energy crisis. The correlations within the Energy sector remained high for a longer period than the correlation within other industries after the crisis of 2008.

Since 2003, the price of the oil barrel (in US dollars) had been growing, and by July 2008, the price spiked, falling strongly after the Subprime Mortgage Crisis. Some reasons suggested for the growing trend before 2008 were the fall of the value of the dollar with respect to other currencies and the excess of demand for energy in a world where various economies were growing fast, together with a fear of limited supply by producers.

Both figures for In Transfer Entropy and Out Transfer Entropy are very similar, what implies that the Transfer Entropy matrix from lagged stocks to original ones (Sector 21) is rather symmetric, what can be also seen from the apparent symmetry of Figure 6. The TE_{in} ranges from 0.0127 to 0.5298 and the TE_{out} ranges from 0.0138 to 0.4535. So, the minimum and maximum values of TE_{out} are slightly smaller than the minimum and maximum values of TE_{in} . Again, the mean in and out TEs are weaker than the mean correlations in some periods of crises. In the crisis of 2008, both TE and correlation registered peaks, but at the end of 2010, there was an increase in both volatility and correlation without a similar increase in TE. For the end of 2011, there was high correlation and medium volatility and TE.

7 Simulations with the network based on Transfer Entropy

As stated in the introduction to this article, there is a belief that the network structure of banks influence the way a shock may propagate. Usually, banks that are more connected are the major spreaders of shocks, but a bank that is not so connected, but whose connections are themselves central, can also be the agent of the propagation of a shock. There is also the issue of back-reaction: a shock may influence other banks that, on their turn, may influence back the bank from which the shock started, and one may even obtain self reinforcement, so that a small crisis may trigger a much bigger one.

Here, we are using stock prices (log-returns) in order to study how one stock relates with another. So, we are not analyzing just defaults or just the banking system, but a larger system made of stocks of a diversity of industries of the US economy. In our modeling of the propagation of crises, we shall consider the trigger of a shock as a considerable drop on the value of a stock, like a 30% fall in its value. This shock then propagates on the network as a factor of the original shock being applied to its neighbors (all stocks, in our case), and we shall consider this factor to be proportional to the TE from the stock to each of its neighbors. We shall be using the network built on TE and not on correlation because we want the shocks to propagate from one day to another (we shall assume a day as our unit of time). In order to avoid influence from one stock to itself on the next day, what would lead to self reinforcement of effects, we set the main diagonal elements of the TE matrix for Sector 21 to zero.

Also, in order to make the effect of shocks decrease in time, we will multiply each iteration by a negative exponential. Our model for the propagation of shocks may be described by the following equation:

$$V_{i,t+1} = \sum_{j=1}^N V_{j,t}^T MTE_{ij} e^{-(t+1)}, \quad (13)$$

where $V_{j,t}^T$ is the transpose of the volatility (absolute value of the log-return) of stock j at time t , $V_{i,t+1}$ is the volatility of stock i at time $t + 1$ (units of one day), and MTE_{ij} is the Transfer Entropy from i to j (from lagged to original variables) with the main diagonal set to zero. So, the volatility of a stock on the following day will depend on the sum of the transfer entropies of all other stocks, multiplied by the volatilities of those stocks on the previous day, times a decreasing exponential factor.

This is a very crude model, which does not take into account a diversity of factors, like the reaction of prices when they have a fall or rise that is beyond the value that the market sees fit for a stock, or the capacity of some stocks of absorbing shocks, but it gives some interesting enough results for the propagation of shocks in a real network of stocks.

In order to use our model for the observation of the propagation of shocks, we shall start with all volatilities set to zero and set one of them as 0.3, which would be equivalent to a large fall (or rise) of the stock of the company. Then, we calculate the volatilities of all stocks, including the original one, by using (13). The results are then used in the calculation of the next period of time and so on, until the shock has subsided. We do this for all stocks in the sample, each one starting its own shock, and analyze the differences in the propagation of the shocks.

Figure 19 shows the effect of a shock starting with the J. P. Morgan (bank), with Exxon Mobil (oil & gas), and with Microsoft (computer software). The graphs show a three dimensional view of the volatility in time according to stock. We can see that the shocks propagate very rapidly to all stocks, but they hit different sectors with distinct strengths. According to the simulations, a high volatility in the stocks of Exxon Mobil (oil & gas) would cause a greater shock than a similar volatility in the stocks of the J. P. Morgan, and a high volatility in the stocks of Microsoft (computer software) would lead to an average propagation when comparing to the two other stocks.

Figure 20 shows the propagation of a shock to the J. P. Morgan bank on the network built using correlation, which is very similar to the network obtained with TE, but which is built without the need for manually imposing constraints. Higher volatility is represented by darker dots and lower volatility is represented by brighter dots. The shock starting at the Financial sector spreads to all sectors, with low intensity first, and then causes an increasing wave of volatility that concentrates on the densely populated region involving most sectors, but mainly the Industrial, Communications and Technology sectors, fading away after that. Although our model is rather crude, it replicates the behavior that can be observed from the volatilities in Figure 11, where a rise in one particular sector (Financial, in that case) rapidly propagates to all other stocks.

As the shocks reach their heights at day 4, we shall use the average volatility at this day as a measure of how strong is the wave produced by the shock in one stock. We shall call this measure Shock Propagation Strength. Table 8 shows the top 10 stocks according to this measure, their company names, sectors, and industries. Most belong to the Technology and Communications sectors, which are some of the most central in the network. So, although they do not have the largest Node Strengths, or In and Out Node Strengths, they are reasonably central in a region of central nodes. Belonging to a more populated area of the network, they are the most likely ones to propagate shocks when we consider our crude model.

Node Strength	Company	Sector	Industry
0.217	Hewlett-Packard Co	Technology	Computers
0.214	Corning Inc	Communications	Telecommunications
0.210	Cliffs Natural Resources Inc	Basic Materials	Iron/Steel
0.209	Western Digital Corp	Technology	Computers
0.208	Dell Inc	Technology	Computers
0.206	Frontier Communications Corp	Communications	Telecommunications
0.205	Symantec Corp	Communications	Internet
0.205	Sirius XM Holdings Inc	Communications	Telecommunications
0.204	Amphenol Corp	Industrial	Electronics
0.203	Nucor Corp	Basic Materials	Iron/Steel

Table 8. Classification of stocks with highest Shock Propagation Strength, their sector and industry classifications. Only the ten stocks with highest values are shown.

We may also apply a systemic shock to all stocks by setting, for example, all volatilities to 0.1, or apply shocks to sectors. Figure 21 shows the effects of shocks of intensity 0.1 to, respectively, all stocks, stocks of the Financial sector, and stocks of the Technology sector. Due to the rapid spread of shocks in the network and to the model used, all figures look similar, expect for scale, that is much higher if the shock is applied to all stocks, and similar in the case of the shock being applied to the Financial or to the Technology sectors.

Because of the way the simulation was constructed, stocks that are more influential in terms of having high Out Node Strengths, and which “live” in regions where stocks are also more connected are the most likely ones to disseminate a crisis. Other types of models would lead to different results, but they closely follow other results based on other types of network models which only include banks or other financial institutions.

In order to close this article, we would like to show some figures that depict the Node Strengths and Shock Propagation Strength on the network formed by correlations, all represent in Figure 20. The dots represent the positions occupied by stocks in the network, which is the same type of graph obtained in Figure 9. Darker colors represent higher values of the measures being depicted and brighter colors represent lower values for these measures. The first graph shows the Node Strength, derived from correlations, and the second and third graphs show the In and Out Node Strengths derived from Transfer Entropy. The last graph shows the Shock Propagation Strength, calculated in this section. Node Strength spreads mostly evenly among stocks, and In and Out Node Strengths tend to concentrate in the Financial sector. Now, the Shock Propagation Strength concentrates in regions of high concentrations of nodes.

8 Conclusions

The two networks built using the correlations between stocks of the US stock market and using the Transfer Entropy from stocks in one day to stocks on the next day proved to be very similar, indicating that a large exchange of information between stocks from one day to another is associated with their similar behavior on this next day. We could see the importance of some sectors of the US economy in the dissemination of information, like the Financial and the Industrial sectors, and the role of receivers of information like the Utilities and Energy sectors. By using moving windows, we could see how correlation and Transfer Entropy rise in times of crises and how correlation has been growing after the crisis of 2008, what did not happen to Transfer Entropy. By building a model based on Transfer Entropy, we could simulate how volatility may propagate in a network of stocks and how sectors that occupy more central positions, like the Communications and Technology sectors, have major roles in the propagation of crises. Some future work will involve working with high frequency data and developing better models for the spread of crises.

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A List of stocks

	Ticker	Company	Sector	Industry	Sub-Industry
1	MON	Monsanto Co (MON)	Basic Materials	Chemicals	Agricultural Chemicals
2	MOS	Mosaic Co/The (MOS)	Basic Materials	Chemicals	Agricultural Chemicals
3	DOW	Dow Chemical Co/The (DOW)	Basic Materials	Chemicals	Chemicals-Diversified
4	DD	El du Pont de Nemours & Co (DD)	Basic Materials	Chemicals	Chemicals-Diversified
5	FMC	FMC Corp (FMC)	Basic Materials	Chemicals	Chemicals-Diversified
6	PPG	PPG Industries Inc (PPG)	Basic Materials	Chemicals	Chemicals-Diversified
7	EMN	Eastman Chemical Co (EMN)	Basic Materials	Chemicals	Chemicals-Specialty
8	ECL	Ecolab Inc (ECL)	Basic Materials	Chemicals	Chemicals-Specialty
9	IFF	International Flavors & Fragrances Inc (IFF)	Basic Materials	Chemicals	Chemicals-Specialty
10	SIAL	Sigma-Aldrich Corp (SIAL)	Basic Materials	Chemicals	Chemicals-Specialty
11	SHW	Sherwin-Williams Co/The (SHW)	Basic Materials	Chemicals	Coatings/Paint
12	APD	Air Products & Chemicals Inc (APD)	Basic Materials	Chemicals	Industrial Gases
13	ARG	Airgas Inc (ARG)	Basic Materials	Chemicals	Industrial Gases
14	PX	Praxair Inc (PX)	Basic Materials	Chemicals	Industrial Gases
15	IP	International Paper Co (IP)	Basic Materials	Forest Products & Paper	Paper & Related Products
16	MWV	MeadWestvaco Corp (MWV)	Basic Materials	Forest Products & Paper	Paper & Related Products
17	CLF	Cliffs Natural Resources Inc (CLF)	Basic Materials	Iron / Steel	Metal-Iron
18	NUE	Nucor Corp (NUE)	Basic Materials	Iron / Steel	Steel-Producers
19	X	United States Steel Corp (X)	Basic Materials	Iron / Steel	Steel-Producers
20	TIE	Titanium Metals Corp (TIE)	Basic Materials	Iron / Steel	Steel-Producers
21	ATI	Allegheny Technologies Inc (ATI)	Basic Materials	Iron / Steel	Steel-Specialty
22	NEM	Newmont Mining Corp (NEM)	Basic Materials	Mining	Gold Mining
23	GOLD	Randgold Resources Ltd (GOLD)	Basic Materials	Mining	Gold Mining
24	AA	Alcoa Inc (AA)	Basic Materials	Mining	Metal-Aluminum
25	FCX	Freeport-McMoRan Copper & Gold Inc (FCX)	Basic Materials	Mining	Metal-Copper
26	VMC	Vulcan Materials Co (VMC)	Basic Materials	Mining	Quarrying
27	CNX	CONSOL Energy Inc (CNX)	Energy	Coal	Coal
28	BTU	Peabody Energy Corp (BTU)	Energy	Coal	Coal
29	APC	Anadarko Petroleum Corp (APC)	Energy	Oil & Gas	Oil Comp-Explor & Prodn
30	APA	Apache Corp (APA)	Energy	Oil & Gas	Oil Comp-Explor & Prodn
31	COG	Cabot Oil & Gas Corp (COG)	Energy	Oil & Gas	Oil Comp-Explor & Prodn
32	CHK	Chesapeake Energy Corp (CHK)	Energy	Oil & Gas	Oil Comp-Explor & Prodn
33	DNR	Denbury Resources Inc (DNR)	Energy	Oil & Gas	Oil Comp-Explor & Prodn
34	DVN	Devon Energy Corp (DVN)	Energy	Oil & Gas	Oil Comp-Explor & Prodn
35	EOG	EOG Resources Inc (EOG)	Energy	Oil & Gas	Oil Comp-Explor & Prodn
36	NFX	Newfield Exploration Co (NFX)	Energy	Oil & Gas	Oil Comp-Explor & Prodn
37	NBL	Noble Energy Inc (NBL)	Energy	Oil & Gas	Oil Comp-Explor & Prodn
38	OXY	Occidental Petroleum Corp (OXY)	Energy	Oil & Gas	Oil Comp-Explor & Prodn
39	PXD	Pioneer Natural Resources Co (PXD)	Energy	Oil & Gas	Oil Comp-Explor & Prodn
40	RRC	Range Resources Corp (RRC)	Energy	Oil & Gas	Oil Comp-Explor & Prodn
41	SWN	Southwestern Energy Co (SWN)	Energy	Oil & Gas	Oil Comp-Explor & Prodn
42	EQT	EQT Corp (EQT)	Energy	Oil & Gas	Oil Comp-Explor & Prodn
43	CVX	Chevron Corp (CVX)	Energy	Oil & Gas	Oil Comp-Integrated
44	COP	ConocoPhillips (COP)	Energy	Oil & Gas	Oil Comp-Integrated
45	XOM	Exxon Mobil Corp (XOM)	Energy	Oil & Gas	Oil Comp-Integrated
46	HES	Hess Corp (HES)	Energy	Oil & Gas	Oil Comp-Integrated
47	MRO	Marathon Oil Corp (MRO)	Energy	Oil & Gas	Oil Comp-Integrated
48	MUR	Murphy Oil Corp (MUR)	Energy	Oil & Gas	Oil Comp-Integrated
49	TSO	Tesoro Corp (TSO)	Energy	Oil & Gas	Oil Refining & Marketing
50	VLO	Valero Energy Corp (VLO)	Energy	Oil & Gas	Oil Refining & Marketing
51	DO	Diamond Offshore Drilling Inc (DO)	Energy	Oil & Gas	Oil & Gas Drilling
52	HP	Helmerich & Payne Inc (HP)	Energy	Oil & Gas	Oil & Gas Drilling
53	NBR	Nabors Industries Ltd (NBR)	Energy	Oil & Gas	Oil & Gas Drilling
54	NE	Noble Corp (NE)	Energy	Oil & Gas	Oil & Gas Drilling
55	RDC	Rowan Cos Plc (RDC)	Energy	Oil & Gas	Oil & Gas Drilling
56	CAM	Cameron International Corp (CAM)	Energy	Oil & Gas Services	Oil Field Mach & Equip
57	FTI	FMC Technologies Inc (FTI)	Energy	Oil & Gas Services	Oil Field Mach & Equip
58	NOV	National Oilwell Varco Inc (NOV)	Energy	Oil & Gas Services	Oil Field Mach & Equip
59	BHI	Baker Hughes Inc (BHI)	Energy	Oil & Gas Services	Oil-Field Services
60	HAL	Halliburton Co (HAL)	Energy	Oil & Gas Services	Oil-Field Services
61	SLB	Schlumberger Ltd (SLB)	Energy	Oil & Gas Services	Oil-Field Services
62	WMB	Williams Cos Inc/The (WMB)	Energy	Pipelines	Pipelines
63	OKE	ONEOK Inc (OKE)	Energy	Pipelines	Pipelines
64	BA	Boeing Co/The (BA)	Industrial	Aerospace/Defense	Aerospace/Defense
65	GD	General Dynamics Corp (GD)	Industrial	Aerospace/Defense	Aerospace/Defense
66	LMT	Lockheed Martin Corp (LMT)	Industrial	Aerospace/Defense	Aerospace/Defense
67	NOC	Northrop Grumman Corp (NOC)	Industrial	Aerospace/Defense	Aerospace/Defense
68	RTN	Raytheon Co (RTN)	Industrial	Aerospace/Defense	Aerospace/Defense
69	COL	Rockwell Collins Inc (COL)	Industrial	Aerospace/Defense	Aerospace/Defense
70	UTX	United Technologies Corp (UTX)	Industrial	Aerospace/Defense	Aerospace/Defense-Equip
71	LLL	L 3 Communications Holdings Inc (LLL)	Industrial	Aerospace / Defense	Electronics-Military
72	MAS	Masco Corp (MAS)	Industrial	Building Materials	Bldg Prod-Wood
73	EMR	Emerson Electric Co (EMR)	Industrial	Electrical Comp. & Equip.	Electric Products-Misc
74	MOLX	Molex Inc (MOLX)	Industrial	Electrical Comp. & Equip.	Electric Products-Misc
75	JBL	Jabil Circuit Inc (JBL)	Industrial	Electronics	Electronic Compo-Misc
76	GRMN	Garmin Ltd (GRMN)	Industrial	Electronics	Electronic Compo-Misc
77	APH	Amphenol Corp (APH)	Industrial	Electronics	Electronic Connectors
78	A	Agilent Technologies Inc (A)	Industrial	Electronics	Electronic Measur Instr
79	FLIR	FLIR Systems Inc (FLIR)	Industrial	Electronics	Electronic Measur Instr
80	TYC	Tyco International Ltd (TYC)	Industrial	Electronics	Electronic Secur Devices
81	HON	Honeywell International Inc (HON)	Industrial	Electronics	Instruments-Controls
82	PKI	PerkinElmer Inc (PKI)	Industrial	Electronics	Instruments-Scientific
83	TMO	Thermo Fisher Scientific Inc (TMO)	Industrial	Electronics	Instruments-Scientific
84	WAT	Waters Corp (WAT)	Industrial	Electronics	Instruments-Scientific
85	FLR	Fluor Corp (FLR)	Industrial	Engineering & Construction	Engineering/R & D Services
86	JEC	Jacobs Engineering Group Inc (JEC)	Industrial	Engineering & Construction	Engineering/R & D Services
87	SRCL	Stericycle Inc (SRCL)	Industrial	Environmental Control	Hazardous Waste Disposal
88	RSR	Republic Services Inc (RSR)	Industrial	Environmental Control	Non-hazardous Waste Disp
89	WM	Waste Management Inc (WM)	Industrial	Environmental Control	Non-hazardous Waste Disp
90	SNA	Snap-on Inc (SNA)	Industrial	Hand / Machine Tools	Tools-Hand Held
91	SWK	Stanley Black & Decker Inc (SWK)	Industrial	Hand / Machine Tools	Tools-Hand Held
92	CAT	Caterpillar Inc (CAT)	Industrial	Machinery - Constr. & Min.	Machinery-Constr & Mining
93	JOY	Joy Global Inc (JOY)	Industrial	Machinery - Constr. & Min.	Machinery-Constr & Mining
94	CMR	Cummins Inc (CMR)	Industrial	Machinery - Diversified	Engines-Internal Combust
95	ROK	Rockwell Automation Inc (ROK)	Industrial	Machinery - Diversified	Industrial Automat/Robot
96	DE	Deere & Co (DE)	Industrial	Machinery - Diversified	Machinery-Farm
97	ROP	Roper Industries Inc (ROP)	Industrial	Machinery - Diversified	Machinery-General Indust

	Ticker	Company	Sector	Industry	Sub-Industry
98	FLS	Flowservice Corp (FLS)	Industrial	Machinery - Diversified	Machinery-Pumps
99	PCP	Precision Castparts Corp (PCP)	Industrial	Metal Fabricate / Hardware	Metal Processors & Fabrica
100	LEG	Leggett & Platt Inc (LEG)	Industrial	Miscellaneous Manufacturing	Diversified Manufact Op
101	MMM	3M Co (MMM)	Industrial	Miscellaneous Manufacturing	Diversified Manufact Op
102	DHR	Danaher Corp (DHR)	Industrial	Miscellaneous Manufacturing	Diversified Manufact Op
103	DOV	Dover Corp (DOV)	Industrial	Miscellaneous Manufacturing	Diversified Manufact Op
104	ETN	Eaton Corp PLC (ETN)	Industrial	Miscellaneous Manufacturing	Diversified Manufact Op
105	GE	General Electric Co (GE)	Industrial	Miscellaneous Manufacturing	Diversified Manufact Op
106	ITW	Illinois Tool Works Inc (ITW)	Industrial	Miscellaneous Manufacturing	Diversified Manufact Op
107	IR	Ingersoll-Rand PLC (IR)	Industrial	Miscellaneous Manufacturing	Diversified Manufact Op
108	PH	Parker Hannifin Corp (PH)	Industrial	Miscellaneous Manufacturing	Diversified Manufact Op
109	TXT	Textron Inc (TXT)	Industrial	Miscellaneous Manufacturing	Diversified Manufact Op
110	PLL	Pall Corp (PLL)	Industrial	Miscellaneous Manufacturing	Filtration/Separat Prod
111	BLL	Ball Corp (BLL)	Industrial	Packaging & Containers	Containers-Metal/Glass
112	OI	Owens-Illinois Inc (OI)	Industrial	Packaging & Containers	Containers-Metal/Glass
113	BMS	Bemis Co Inc (BMS)	Industrial	Packaging & Containers	Containers-Paper/Plastic
114	SEE	Sealed Air Corp (SEE)	Industrial	Packaging & Containers	Containers-Paper/Plastic
115	CSX	CSX Corp (CSX)	Industrial	Transportation	Transport-Rail
116	NSC	Norfolk Southern Corp (NSC)	Industrial	Transportation	Transport-Rail
117	UNP	Union Pacific Corp (UNP)	Industrial	Transportation	Transport-Rail
118	CHRW	CH Robinson Worldwide Inc (CHRW)	Industrial	Transportation	Transport-Services
119	EXPD	Expeditors International of Washington Inc (EXPD)	Industrial	Transportation	Transport-Services
120	FDX	FedEx Corp (FDX)	Industrial	Transportation	Transport-Services
121	R	Ryder System Inc (R)	Industrial	Transportation	Transport-Services
122	UPS	United Parcel Service Inc (UPS)	Industrial	Transportation	Transport-Services
123	LUV	Southwest Airlines Co (LUV)	Consumer, Cyclical	Airlines	Airlines
124	COH	Coach Inc (COH)	Consumer, Cyclical	Apparel	Apparel Manufacturers
125	RL	Ralph Lauren Corp (RL)	Consumer, Cyclical	Apparel	Apparel Manufacturers
126	VFC	VF Corp (VFC)	Consumer, Cyclical	Apparel	Apparel Manufacturers
127	NKE	NIKE Inc (NKE)	Consumer, Cyclical	Apparel	Athletic Footwear
128	F	Ford Motor Co (F)	Consumer, Cyclical	Auto Manufacturers	Auto-Cars/Light Trucks
129	PCAR	PACCAR Inc (PCAR)	Consumer, Cyclical	Auto Manufacturers	Auto-Med & Heavy Duty Trks
130	BWA	BorgWarner Inc (BWA)	Consumer, Cyclical	Auto Parts & Equipment	Auto/Trk Prts & Equip-Orig
131	JCI	Johnson Controls Inc (JCI)	Consumer, Cyclical	Auto Parts & Equipment	Auto/Trk Prts & Equip-Orig
132	GT	Goodyear Tire & Rubber Co/The (GT)	Consumer, Cyclical	Auto Parts & Equipment	Rubber-Tires
133	GPC	Genuine Parts Co (GPC)	Consumer, Cyclical	Distribution/Wholesale	Distribution/Wholesale
134	FAST	Fastenal Co (FAST)	Consumer, Cyclical	Distribution/Wholesale	Distribution/Wholesale
135	GWV	WW Grainger Inc (GWV)	Consumer, Cyclical	Distribution/Wholesale	Distribution/Wholesale
136	FOSL	Fossil Inc (FOSL)	Consumer, Cyclical	Distribution/Wholesale	Distribution/Wholesale
137	IGT	International Game Technology (IGT)	Consumer, Cyclical	Entertainment	Casino Services
138	DHI	DR Horton Inc (DHI)	Consumer, Cyclical	Home Builders	Bldg-Residential/Commer
139	LEN	Lennar Corp (LEN)	Consumer, Cyclical	Home Builders	Bldg-Residential/Commer
140	PHM	PulteGroup Inc (PHM)	Consumer, Cyclical	Home Builders	Bldg-Residential/Commer
141	WHR	Whirlpool Corp (WHR)	Consumer, Cyclical	Home Furnishings	Appliances
142	HAR	Harman International Industries Inc (HAR)	Consumer, Cyclical	Home Furnishings	Audio/Video Products
143	NWL	Newell Rubbermaid Inc (NWL)	Consumer, Cyclical	Housewares	Home Decoration Products
144	CCL	Carnival Corp (CCL)	Consumer, Cyclical	Leisure Time	Cruise Lines
145	HOG	Harley-Davidson Inc (HOG)	Consumer, Cyclical	Leisure Time	Motorcycle/Motor Scooter
146	WYNN	Wynn Resorts Ltd (WYNN)	Consumer, Cyclical	Lodging	Casino Hotels
147	MAR	Marriott International Inc/DE (MAR)	Consumer, Cyclical	Lodging	Hotels & Motels
148	HOT	Starwood Hotels & Resorts Worldwide Inc (HOT)	Consumer, Cyclical	Lodging	Hotels & Motels
149	ANF	Abercrombie & Fitch Co (ANF)	Consumer, Cyclical	Retail	Retail-Apparel/Shoe
150	GPS	Gap Inc/The (GPS)	Consumer, Cyclical	Retail	Retail-Apparel/Shoe
151	LTD	Ltd Brands Inc (LTD)	Consumer, Cyclical	Retail	Retail-Apparel/Shoe
152	ROST	Ross Stores Inc (ROST)	Consumer, Cyclical	Retail	Retail-Apparel/Shoe
153	URBN	Urban Outfitters Inc (URBN)	Consumer, Cyclical	Retail	Retail-Apparel/Shoe
154	AZO	AutoZone Inc (AZO)	Consumer, Cyclical	Retail	Retail-Auto Parts
155	ORLY	O'Reilly Automotive Inc (ORLY)	Consumer, Cyclical	Retail	Retail-Auto Parts
156	AN	AutoNation Inc (AN)	Consumer, Cyclical	Retail	Retail-Automobile
157	KMX	CarMax Inc (KMX)	Consumer, Cyclical	Retail	Retail-Automobile
158	BBBY	Bed Bath & Beyond Inc (BBBY)	Consumer, Cyclical	Retail	Retail-Bedding
159	HD	Home Depot Inc/The (HD)	Consumer, Cyclical	Retail	Retail-Building Products
160	LOW	Lowe's Cos Inc (LOW)	Consumer, Cyclical	Retail	Retail-Building Products
161	GME	GameStop Corp (GME)	Consumer, Cyclical	Retail	Retail-Computer Equip
162	BBY	Best Buy Co Inc (BBY)	Consumer, Cyclical	Retail	Retail-Consumer Electron
163	BIG	Big Lots Inc (BIG)	Consumer, Cyclical	Retail	Retail-Discount
164	DLTR	Dollar Tree Inc (DLTR)	Consumer, Cyclical	Retail	Retail-Discount
165	FDO	Family Dollar Stores Inc (FDO)	Consumer, Cyclical	Retail	Retail-Discount
166	TGT	Target Corp (TGT)	Consumer, Cyclical	Retail	Retail-Discount
167	COST	Costco Wholesale Corp (COST)	Consumer, Cyclical	Retail	Retail-Discount
168	WMT	Wal-Mart Stores Inc (WMT)	Consumer, Cyclical	Retail	Retail-Discount
169	CVS	CVS Caremark Corp (CVS)	Consumer, Cyclical	Retail	Retail-Drug Store
170	WAG	Walgreen Co (WAG)	Consumer, Cyclical	Retail	Retail-Drug Store
171	TIF	Tiffany & Co (TIF)	Consumer, Cyclical	Retail	Retail-Jewelry
172	JWN	Nordstrom Inc (JWN)	Consumer, Cyclical	Retail	Retail-Major Dept Store
173	JCP	JC Penney Co Inc (JCP)	Consumer, Cyclical	Retail	Retail-Major Dept Store
174	TJX	TJX Cos Inc (TJX)	Consumer, Cyclical	Retail	Retail-Major Dept Store
175	SPLS	Staples Inc (SPLS)	Consumer, Cyclical	Retail	Retail-Office Supplies
176	KSS	Kohl's Corp (KSS)	Consumer, Cyclical	Retail	Retail-Regnl Dept Store
177	M	Macy's Inc (M)	Consumer, Cyclical	Retail	Retail-Regnl Dept Store
178	DRI	Darden Restaurants Inc (DRI)	Consumer, Cyclical	Retail	Retail-Restaurants
179	MCD	McDonald's Corp (MCD)	Consumer, Cyclical	Retail	Retail-Restaurants
180	SBUX	Starbucks Corp (SBUX)	Consumer, Cyclical	Retail	Retail-Restaurants
181	YUM	Yum! Brands Inc (YUM)	Consumer, Cyclical	Retail	Retail-Restaurants
182	CTAS	Cintas Corp (CTAS)	Consumer, Cyclical	Textyles	Linen Supply & Rel Items
183	HAS	Hasbro Inc (HAS)	Consumer, Cyclical	Toys / Games / Hobbies	Toys
184	MAT	Mattel Inc (MAT)	Consumer, Cyclical	Toys / Games / Hobbies	Toys
185	LUK	Leucadia National Corp (LUK)	Diversified	Holding Companies - Diversified	Diversified Operations
186	TRV	Two Rivers Financial Group Inc (TRVR)	Financial	Banks	Commer Banks-Central US
187	MTB	M & T Bank Corp (MTB)	Financial	Banks	Commer Banks-Eastern US
188	BBT	BB & T Corp (BBT)	Financial	Banks	Commer Banks-Southern US
189	FHN	First Horizon National Corp (FHN)	Financial	Banks	Commer Banks-Southern US
190	RF	Regions Financial Corp (RF)	Financial	Banks	Commer Banks-Southern US
191	ZION	Zions Bancorporation (ZION)	Financial	Banks	Commer Banks-Southern US
192	BAC	Bank of America Corp (BAC)	Financial	Banks	Diversified Banking Inst
193	C	Citigroup Inc (C)	Financial	Banks	Diversified Banking Inst
194	GS	Goldman Sachs Group Inc/The (GS)	Financial	Banks	Diversified Banking Inst
195	JPM	JPMorgan Chase & Co (JPM)	Financial	Banks	Diversified Banking Inst

	Ticker	Company	Sector	Industry	Sub-Industry
196	MS	Morgan Stanley (MS)	Financial	Banks	Diversified Banking Inst
197	BK	Bank of New York Mellon Corp/The (BK)	Financial	Banks	Fiduciary Banks
198	NTRS	Northern Trust Corp (NTRS)	Financial	Banks	Fiduciary Banks
199	STT	State Street Corp (STT)	Financial	Banks	Fiduciary Banks
200	COF	Capital One Financial Corp (COF)	Financial	Banks	Super-Regional Banks-US
201	CMA	Comerica Inc (CMA)	Financial	Banks	Super-Regional Banks-US
202	FITB	Fifth Third Bancorp (FITB)	Financial	Banks	Super-Regional Banks-US
203	HBAN	Huntington Bancshares Inc/OH (HBAN)	Financial	Banks	Super-Regional Banks-US
204	KEY	KeyCorp (KEY)	Financial	Banks	Super-Regional Banks-US
205	PNC	PNC Financial Services Group Inc (PNC)	Financial	Banks	Super-Regional Banks-US
206	STI	SunTrust Banks Inc (STI)	Financial	Banks	Super-Regional Banks-US
207	USB	US Bancorp (USB)	Financial	Banks	Super-Regional Banks-US
208	WFC	Wells Fargo & Co (WFC)	Financial	Banks	Super-Regional Banks-US
209	SLM	SLM Corp (SLM)	Financial	Diversified Financial Services	Finance-Consumer Loans
210	AXP	American Express Co (AXP)	Financial	Diversified Financial Services	Finance-Credit Card
211	SCHW	Charles Schwab Corp/The (SCHW)	Financial	Diversified Financial Services	Finance-Invest Bnkr/Brkr
212	ETFC	E*TRADE Financial Corp (ETFC)	Financial	Diversified Financial Services	Finance-Invest Bnkr/Brkr
213	CME	CME Group Inc/IL (CME)	Financial	Diversified Financial Services	Finance-Other Services
214	BLK	BlackRock Inc (BLK)	Financial	Diversified Financial Services	Invest Mgmt/Advis Serv
215	FII	Federated Investors Inc (FII)	Financial	Diversified Financial Services	Invest Mgmt/Advis Serv
216	BEN	Franklin Resources Inc (BEN)	Financial	Diversified Financial Services	Invest Mgmt/Advis Serv
217	IVZ	Invesco Ltd (IVZ)	Financial	Diversified Financial Services	Invest Mgmt/Advis Serv
218	LM	Legg Mason Inc (LM)	Financial	Diversified Financial Services	Invest Mgmt/Advis Serv
219	TROW	T Rowe Price Group Inc (TROW)	Financial	Diversified Financial Services	Invest Mgmt/Advis Serv
220	AON	Aon PLC (AON)	Financial	Insurance	Insurance Brokers
221	MMC	Marsh & McLennan Cos Inc (MMC)	Financial	Insurance	Insurance Brokers
222	AFL	Aflac Inc (AFL)	Financial	Insurance	Life/Health Insurance
223	LNC	Lincoln National Corp (LNC)	Financial	Insurance	Life/Health Insurance
224	PFJ	Principal Financial Group Inc (PFJ)	Financial	Insurance	Life/Health Insurance
225	PRU	Prudential Financial Inc (PRU)	Financial	Insurance	Life/Health Insurance
226	TMK	Torchmark Corp (TMK)	Financial	Insurance	Life/Health Insurance
227	UNM	Unum Group (UNM)	Financial	Insurance	Life/Health Insurance
228	ACE	ACE Ltd (ACE)	Financial	Insurance	Multi-line Insurance
229	ALL	Allstate Corp/The (ALL)	Financial	Insurance	Multi-line Insurance
230	AIG	American International Group Inc (AIG)	Financial	Insurance	Multi-line Insurance
231	CINF	Cincinnati Financial Corp (CINF)	Financial	Insurance	Multi-line Insurance
232	HIG	Hartford Financial Services Group Inc (HIG)	Financial	Insurance	Multi-line Insurance
233	L	Loews Corp (L)	Financial	Insurance	Multi-line Insurance
234	MET	MetLife Inc (MET)	Financial	Insurance	Multi-line Insurance
235	XL	XL Group PLC (XL)	Financial	Insurance	Multi-line Insurance
236	CB	Chubb Corp/The (CB)	Financial	Insurance	Property/Casualty Ins
237	PGR	Progressive Corp/The (PGR)	Financial	Insurance	Property/Casualty Ins
238	BRK/B	Berkshire Hathaway Inc (BRK/B)	Financial	Insurance	Reinsurance
239	AIV	Apartment Investment & Management Co (AIV)	Financial	REITS	REITS-Apartments
240	AVB	AvalonBay Communities Inc (AVB)	Financial	REITS	REITS-Apartments
241	EQR	Equity Residential (EQR)	Financial	REITS	REITS-Apartments
242	PCL	Plum Creek Timber Co Inc (PCL)	Financial	REITS	REITS-Diversified
243	VNO	Vornado Realty Trust (VNO)	Financial	REITS	REITS-Diversified
244	WY	Weyerhaeuser Co (WY)	Financial	REITS	REITS-Diversified
245	AMT	American Tower Corp (AMT)	Financial	REITS	REITS-Diversified
246	HCP	HCP Inc (HCP)	Financial	REITS	REITS-Health Care
247	HCN	Health Care REIT Inc (HCN)	Financial	REITS	REITS-Health Care
248	VTR	Ventas Inc (VTR)	Financial	REITS	REITS-Health Care
249	HST	Host Hotels & Resorts Inc (HST)	Financial	REITS	REITS-Hotels
250	BXP	Boston Properties Inc (BXP)	Financial	REITS	REITS-Office Property
251	SPG	Simon Property Group Inc (SPG)	Financial	REITS	REITS-Regional Malls
252	KIM	Kimco Realty Corp (KIM)	Financial	REITS	REITS-Shopping Centers
253	PSA	Public Storage (PSA)	Financial	REITS	REITS-Storage
254	PLD	Prologis Inc (PLD)	Financial	REITS	REITS-Warehouse/Industr
255	HCBK	Hudson City Bancorp Inc (HCBK)	Financial	Savings & Loans	S & L/Thrfts-Eastern US
256	PBCT	People's United Financial Inc (PBCT)	Financial	Savings & Loans	S & L/Thrfts-Eastern US
257	IPG	Interpublic Group of Cos Inc/The (IPG)	Communications	Advertising	Advertising Agencies
258	OMC	Omnicom Group Inc (OMC)	Communications	Advertising	Advertising Agencies
259	AMZN	Amazon.com Inc (AMZN)	Communications	Internet	E-Commerce/Products
260	EBAY	eBay Inc (EBAY)	Communications	Internet	E-Commerce/Products
261	NFLX	Netflix Inc (NFLX)	Communications	Internet	E-Commerce/Products
262	PCLN	priceline.com Inc (PCLN)	Communications	Internet	E-Commerce/Services
263	FFIV	F5 Networks Inc (FFIV)	Communications	Internet	Internet Infrastr Sftwr
264	SYMC	Symantec Corp (SYMC)	Communications	Internet	Internet Security
265	VRSN	VeriSign Inc (VRSN)	Communications	Internet	Internet Security
266	YHOO	Yahoo! Inc (YHOO)	Communications	Internet	Web Portals/ISP
267	CVC	Cablevision Systems Corp (CVC)	Communications	Media	Cable/Satellite TV
268	CMCSA	Comcast Corp (CMCSA)	Communications	Media	Cable/Satellite TV
269	DTV	DIRECTV (DTV)	Communications	Media	Cable/Satellite TV
270	NWSA	News Corp (NWSA)	Communications	Media	Multimedia
271	TWX	Time Warner Inc (TWX)	Communications	Media	Multimedia
272	DIS	Walt Disney Co/The (DIS)	Communications	Media	Multimedia
273	MHP	McGraw-Hill Cos Inc/The (MHP)	Communications	Media	Publishing-Books
274	GCI	Gannett Co Inc (GCI)	Communications	Media	Publishing-Newspapers
275	WPO	Washington Post Co/The (WPO)	Communications	Media	Publishing-Newspapers
276	SIRI	Sirius XM Radio Inc (SIRI)	Communications	Media	Radio
277	CBS	CBS Corp (CBS)	Communications	Media	Television
278	S	Sprint Nextel Corp (S)	Communications	Telecommunications	Cellular Telecom
279	VOD	Vodafone Group PLC (VOD)	Communications	Telecommunications	Cellular Telecom
280	CSCO	Cisco Systems Inc (CSCO)	Communications	Telecommunications	Networking Products
281	GLW	Corning Inc (GLW)	Communications	Telecommunications	Telecom Eq Fiber Optics
282	JDSU	JDS Uniphase Corp (JDSU)	Communications	Telecommunications	Telecom Eq Fiber Optics
283	HRS	Harris Corp (HRS)	Communications	Telecommunications	Telecommunication Equip
284	JNPR	Juniper Networks Inc (JNPR)	Communications	Telecommunications	Telecommunication Equip
285	T	AT & T Inc (T)	Communications	Telecommunications	Telephone-Integrated
286	CTL	CenturyLink Inc (CTL)	Communications	Telecommunications	Telephone-Integrated
287	FTR	Frontier Communications Corp (FTR)	Communications	Telecommunications	Telephone-Integrated
288	VZ	Verizon Communications Inc (VZ)	Communications	Telecommunications	Telephone-Integrated
289	MSI	Motorola Solutions Inc (MSI)	Communications	Telecommunications	Wireless Equipment
290	SBAC	SBA Communications Corp (SBAC)	Communications	Telecommunications	Wireless Equipment
291	ACN	Accenture PLC (ACN)	Technology	Computers	Computer Services
292	CTSH	Cognizant Technology Solutions Corp (CTSH)	Technology	Computers	Computer Services
293	CSC	Computer Sciences Corp (CSC)	Technology	Computers	Computer Services

	Ticker	Company	Sector	Industry	Sub-Industry
294	IBM	International Business Machines Corp (IBM)	Technology	Computers	Computer Services
295	AAPL	Apple Inc (AAPL)	Technology	Computers	Computers
296	DELL	Dell Inc (DELL)	Technology	Computers	Computers
297	HPQ	Hewlett-Packard Co (HPQ)	Technology	Computers	Computers
298	EMC	EMC Corp/MA (EMC)	Technology	Computers	Computers-Memory Devices
299	NTAP	NetApp Inc (NTAP)	Technology	Computers	Computers-Memory Devices
300	SNDK	SanDisk Corp (SNDK)	Technology	Computers	Computers-Memory Devices
301	WDC	Western Digital Corp (WDC)	Technology	Computers	Computers-Memory Devices
302	STX	Seagate Technology PLC (STX)	Technology	Computers	Computers-Memory Devices
303	LXK	Lexmark International Inc (LXK)	Technology	Computers	Computers-Peripher Equip
304	PBI	Pitney Bowes Inc (PBI)	Technology	Office / Business Equipment	Office Automation & Equip
305	XRX	Xerox Corp (XRX)	Technology	Office / Business Equipment	Office Automation & Equip
306	AMD	Advanced Micro Devices Inc (AMD)	Technology	Semiconductors	Electronic Compo-Semicon
307	ALTR	Altera Corp (ALTR)	Technology	Semiconductors	Electronic Compo-Semicon
308	BRCM	Broadcom Corp (BRCM)	Technology	Semiconductors	Electronic Compo-Semicon
309	INTC	Intel Corp (INTC)	Technology	Semiconductors	Electronic Compo-Semicon
310	LSI	LSI Corp (LSI)	Technology	Semiconductors	Electronic Compo-Semicon
311	MCHP	Microchip Technology Inc (MCHP)	Technology	Semiconductors	Electronic Compo-Semicon
312	MU	Micron Technology Inc (MU)	Technology	Semiconductors	Electronic Compo-Semicon
313	NVDA	NVIDIA Corp (NVDA)	Technology	Semiconductors	Electronic Compo-Semicon
314	TXN	Texas Instruments Inc (TXN)	Technology	Semiconductors	Electronic Compo-Semicon
315	XLNX	Xilinx Inc (XLNX)	Technology	Semiconductors	Electronic Compo-Semicon
316	ADI	Analog Devices Inc (ADI)	Technology	Semiconductors	Semicon Compo-Intg Circu
317	LLTC	Linear Technology Corp (LLTC)	Technology	Semiconductors	Semicon Compo-Intg Circu
318	QCOM	QUALCOMM Inc (QCOM)	Technology	Semiconductors	Semicon Compo-Intg Circu
319	MXIM	Maxim Integrated Products Inc (MXIM)	Technology	Semiconductors	Semicon Compo-Intg Circu
320	AMAT	Applied Materials Inc (AMAT)	Technology	Semiconductors	Semiconductor Equipment
321	KLAC	KLA-Tencor Corp (KLAC)	Technology	Semiconductors	Semiconductor Equipment
322	TER	Teradyne Inc (TER)	Technology	Semiconductors	Semiconductor Equipment
323	CTXS	Citrix Systems Inc (CTXS)	Technology	Software	Applications Software
324	CPWR	Compuware Corp (CPWR)	Technology	Software	Applications Software
325	INTU	Intuit Inc (INTU)	Technology	Software	Applications Software
326	MSFT	Microsoft Corp (MSFT)	Technology	Software	Applications Software
327	RHT	Red Hat Inc (RHT)	Technology	Software	Applications Software
328	CHKP	Check Point Software Technologies Ltd (CHKP)	Technology	Software	Applications Software
329	NUAN	Nuance Communications Inc (NUAN)	Technology	Software	Applications Software
330	ADSK	Autodesk Inc (ADSK)	Technology	Software	Computer Aided Design
331	AKAM	Akamai Technologies Inc (AKAM)	Technology	Software	Computer Software
332	DNB	Dun & Bradstreet Corp/The (DNB)	Technology	Software	Data Processing/Mgmt
333	FIS	Fidelity National Information Services Inc (FIS)	Technology	Software	Data Processing/Mgmt
334	FISV	Fiserv Inc (FISV)	Technology	Software	Data Processing/Mgmt
335	ADBE	Adobe Systems Inc (ADBE)	Technology	Software	Electronic Forms
336	BMC	BMC Software Inc (BMC)	Technology	Software	Enterprise Software/Serv
337	CA	CA Inc (CA)	Technology	Software	Enterprise Software/Serv
338	ORCL	Oracle Corp (ORCL)	Technology	Software	Enterprise Software/Serv
339	EA	Electronic Arts Inc (EA)	Technology	Software	Entertainment Software
340	ATVI	Activision Blizzard Inc (ATVI)	Technology	Software	Entertainment Software
341	CERN	Cerner Corp (CERN)	Technology	Software	Medical Information Sys
342	AES	AES Corp/VA (AES)	Utilities	Electric	Electric-Generation
343	AEE	Ameren Corp (AEE)	Utilities	Electric	Electric-Integrated
344	AEP	American Electric Power Co Inc (AEP)	Utilities	Electric	Electric-Integrated
345	CMS	CMS Energy Corp (CMS)	Utilities	Electric	Electric-Integrated
346	ED	Consolidated Edison Inc (ED)	Utilities	Electric	Electric-Integrated
347	D	Dominion Resources Inc/VA (D)	Utilities	Electric	Electric-Integrated
348	DTE	DTE Energy Co (DTE)	Utilities	Electric	Electric-Integrated
349	DUK	Duke Energy Corp (DUK)	Utilities	Electric	Electric-Integrated
350	EIX	Edison International (EIX)	Utilities	Electric	Electric-Integrated
351	ETR	Entergy Corp (ETR)	Utilities	Electric	Electric-Integrated
352	EXC	Exelon Corp (EXC)	Utilities	Electric	Electric-Integrated
353	FE	FirstEnergy Corp (FE)	Utilities	Electric	Electric-Integrated
354	TEG	Integrus Energy Group Inc (TEG)	Utilities	Electric	Electric-Integrated
355	NEE	NextEra Energy Inc (NEE)	Utilities	Electric	Electric-Integrated
356	NU	Northeast Utilities (NU)	Utilities	Electric	Electric-Integrated
357	POM	Pepco Holdings Inc (POM)	Utilities	Electric	Electric-Integrated
358	PCG	PG & E Corp (PCG)	Utilities	Electric	Electric-Integrated
359	PNW	Pinnacle West Capital Corp (PNW)	Utilities	Electric	Electric-Integrated
360	PPL	PPL Corp (PPL)	Utilities	Electric	Electric-Integrated
361	PEG	Public Service Enterprise Group Inc (PEG)	Utilities	Electric	Electric-Integrated
362	SCG	SCANA Corp (SCG)	Utilities	Electric	Electric-Integrated
363	SO	Southern Co/The (SO)	Utilities	Electric	Electric-Integrated
364	TE	TECO Energy Inc (TE)	Utilities	Electric	Electric-Integrated
365	WEC	Wisconsin Energy Corp (WEC)	Utilities	Electric	Electric-Integrated
366	XEL	Xcel Energy Inc (XEL)	Utilities	Electric	Electric-Integrated
367	GAS	AGL Resources Inc (GAS)	Utilities	Gas	Gas-Distribution
368	CNP	CenterPoint Energy Inc (CNP)	Utilities	Gas	Gas-Distribution
369	NI	NiSource Inc (NI)	Utilities	Gas	Gas-Distribution
370	SRE	Sempra Energy (SRE)	Utilities	Gas	Gas-Distribution
371	ADM	Archer-Daniels-Midland Co (ADM)	Consumer, Non-Cyclical	Agriculture	Agricultural Operations
372	MO	Altria Group Inc (MO)	Consumer, Non-Cyclical	Agriculture	Tobacco
373	RAI	Reynolds American Inc (RAI)	Consumer, Non-Cyclical	Agriculture	Tobacco
374	KO	Coca-Cola Co/The (KO)	Consumer, Non-Cyclical	Beverages	Beverages-Non-alcoholic
375	CCE	Coca-Cola Enterprises Inc (CCE)	Consumer, Non-Cyclical	Beverages	Beverages-Non-alcoholic
376	PEP	PepsiCo Inc (PEP)	Consumer, Non-Cyclical	Beverages	Beverages-Non-alcoholic
377	MNST	Monster Beverage Corp (MNST)	Consumer, Non-Cyclical	Beverages	Beverages-Non-alcoholic
378	BEAM	Beam Inc (BEAM)	Consumer, Non-Cyclical	Beverages	Beverages-Wine/Spirits
379	BF/B	Brown-Forman Corp (BF/B)	Consumer, Non-Cyclical	Beverages	Beverages-Wine/Spirits
380	STZ	Constellation Brands Inc (STZ)	Consumer, Non-Cyclical	Beverages	Beverages-Wine/Spirits
381	TAP	Molson Coors Brewing Co (TAP)	Consumer, Non-Cyclical	Beverages	Brewery
382	AMGN	Amgen Inc (AMGN)	Consumer, Non-Cyclical	Biotechnology	Medical-Biomedical/Gene
383	BIIB	Biogen Idec Inc (BIIB)	Consumer, Non-Cyclical	Biotechnology	Medical-Biomedical/Gene
384	CELG	Celgene Corp (CELG)	Consumer, Non-Cyclical	Biotechnology	Medical-Biomedical/Gene
385	GILD	Gilead Sciences Inc (GILD)	Consumer, Non-Cyclical	Biotechnology	Medical-Biomedical/Gene
386	LIFE	Life Technologies Corp (LIFE)	Consumer, Non-Cyclical	Biotechnology	Medical-Biomedical/Gene
387	ALXN	Alexion Pharmaceuticals Inc (ALXN)	Consumer, Non-Cyclical	Biotechnology	Medical-Biomedical/Gene
388	REGN	Regeneron Pharmaceuticals Inc (REGN)	Consumer, Non-Cyclical	Biotechnology	Medical-Biomedical/Gene
389	VRTX	Vertex Pharmaceuticals Inc (VRTX)	Consumer, Non-Cyclical	Biotechnology	Medical-Biomedical/Gene
390	HRB	H & R Block Inc (HRB)	Consumer, Non-Cyclical	Commercial Services	Commercial Serv-Finance
391	EFX	Equifax Inc (EFX)	Consumer, Non-Cyclical	Commercial Services	Commercial Serv-Finance

	Ticker	Company	Sector	Industry	Sub-Industry
392	MCO	Moody's Corp (MCO)	Consumer, Non-Cyclical	Commercial Services	Commercial Serv-Finance
393	ADP	Automatic Data Processing Inc (ADP)	Consumer, Non-Cyclical	Commercial Services	Commercial Serv-Finance
394	PAYX	Paychex Inc (PAYX)	Consumer, Non-Cyclical	Commercial Services	Commercial Serv-Finance
395	TSS	Total System Services Inc (TSS)	Consumer, Non-Cyclical	Commercial Services	Commercial Serv-Finance
396	IRM	Iron Mountain Inc (IRM)	Consumer, Non-Cyclical	Commercial Services	Commercial Services
397	PWR	Quanta Services Inc (PWR)	Consumer, Non-Cyclical	Commercial Services	Commercial Services
398	RHI	Robert Half International Inc (RHI)	Consumer, Non-Cyclical	Commercial Services	Human Resources
399	RRD	RR Donnelley & Sons Co (RRD)	Consumer, Non-Cyclical	Commercial Services	Printing-Commercial
400	APOL	Apollo Group Inc (APOL)	Consumer, Non-Cyclical	Commercial Services	Schools
401	DV	DeVry Inc (DV)&Consumer, Non-Cyclical	Commercial Services	Schools	
402	AVP	Avon Products Inc (AVP)	Consumer, Non-Cyclical	Cosmetics / Personal Care	Cosmetics & Toiletries
403	CL	Colgate-Palmolive Co (CL)	Consumer, Non-Cyclical	Cosmetics / Personal Care	Cosmetics & Toiletries
404	EL	Estee Lauder Cos Inc/The (EL)	Consumer, Non-Cyclical	Cosmetics / Personal Care	Cosmetics & Toiletries
405	PG	Procter & Gamble Co/The (PG)	Consumer, Non-Cyclical	Cosmetics / Personal Care	Cosmetics & Toiletries
406	SJM	JM Smucker Co/The (SJM)	Consumer, Non-Cyclical	Food	Food-Confectionery
407	HSY	Hershey Co/The (HSY)	Consumer, Non-Cyclical	Food	Food-Confectionery
408	DF	Dean Foods Co (DF)	Consumer, Non-Cyclical	Food	Food-Dairy Products
409	HRL	Hormel Foods Corp (HRL)	Consumer, Non-Cyclical	Food	Food-Meat Products
410	HSH	Hillshire Brands Co (HSH)	Consumer, Non-Cyclical	Food	Food-Meat Products
411	TSN	Tyson Foods Inc (TSN)	Consumer, Non-Cyclical	Food	Food-Meat Products
412	CPB	Campbell Soup Co (CPB)	Consumer, Non-Cyclical	Food	Food-Misc/Diversified
413	CAG	ConAgra Foods Inc (CAG)	Consumer, Non-Cyclical	Food	Food-Misc/Diversified
414	GIS	General Mills Inc (GIS)	Consumer, Non-Cyclical	Food	Food-Misc/Diversified
415	HNZ	HJ Heinz Co (HNZ)	Consumer, Non-Cyclical	Food	Food-Misc/Diversified
416	K	Kellogg Co (K)	Consumer, Non-Cyclical	Food	Food-Misc/Diversified
417	MKC	McCormick & Co Inc/MD (MKC)	Consumer, Non-Cyclical	Food	Food-Misc/Diversified
418	KR	Kroger Co/The (KR)	Consumer, Non-Cyclical	Food	Food-Retail
419	SWY	Safeway Inc (SWY)	Consumer, Non-Cyclical	Food	Food-Retail
420	SVU	SUPERVALU Inc (SVU)	Consumer, Non-Cyclical	Food	Food-Retail
421	WFM	Whole Foods Market Inc (WFM)	Consumer, Non-Cyclical	Food	Food-Retail
422	SY	Sysco Corp (SY)	Consumer, Non-Cyclical	Food	Food-Wholesale/Distrib
423	XRAY	DENTSPLY International Inc (XRAY)	Consumer, Non-Cyclical	Health Care - Products	Dental Supplies & Equip
424	PDCO	Patterson Cos Inc (PDCO)	Consumer, Non-Cyclical	Health Care - Products	Dental Supplies & Equip
425	BCR	CR Bard Inc (BCR)	Consumer, Non-Cyclical	Health Care - Products	Disposable Medical Prod
426	BSX	Boston Scientific Corp (BSX)	Consumer, Non-Cyclical	Health Care - Products	Medical Instruments
427	EW	Edwards Lifesciences Corp (EW)	Consumer, Non-Cyclical	Health Care - Products	Medical Instruments
428	ISRG	Intuitive Surgical Inc (ISRG)	Consumer, Non-Cyclical	Health Care - Products	Medical Instruments
429	MDT	Medtronic Inc (MDT)	Consumer, Non-Cyclical	Health Care - Products	Medical Instruments
430	STJ	St Jude Medical Inc (STJ)	Consumer, Non-Cyclical	Health Care - Products	Medical Instruments
431	BAX	Baxter International Inc (BAX)	Consumer, Non-Cyclical	Health Care - Products	Medical Products
432	BDX	Becton Dickinson and Co (BDX)	Consumer, Non-Cyclical	Health Care - Products	Medical Products
433	SYK	Stryker Corp (SYK)	Consumer, Non-Cyclical	Health Care - Products	Medical Products
434	VAR	Varian Medical Systems Inc (VAR)	Consumer, Non-Cyclical	Health Care - Products	Medical Products
435	ZMH	Zimmer Holdings Inc (ZMH)	Consumer, Non-Cyclical	Health Care - Products	Medical Products
436	HSIC	Henry Schein Inc (HSIC)	Consumer, Non-Cyclical	Health Care - Products	Medical Products
437	DVA	DaVita HealthCare Partners Inc (DVA)	Consumer, Non-Cyclical	Health Care - Services	Dialysis Centers
438	LH	Laboratory Corp of America Holdings (LH)	Consumer, Non-Cyclical	Health Care - Services	Medical Labs & Testing Srv
439	DGX	Quest Diagnostics Inc (DGX)	Consumer, Non-Cyclical	Health Care - Services	Medical Labs & Testing Srv
440	AET	Aetna Inc (AET)	Consumer, Non-Cyclical	Health Care - Services	Medical-HMO
441	CI	Cigna Corp (CI)	Consumer, Non-Cyclical	Health Care - Services	Medical-HMO
442	CVH	Coventry Health Care Inc (CVH)	Consumer, Non-Cyclical	Health Care - Services	Medical-HMO
443	HUM	Humana Inc (HUM)	Consumer, Non-Cyclical	Health Care - Services	Medical-HMO
444	UNH	UnitedHealth Group Inc (UNH)	Consumer, Non-Cyclical	Health Care - Services	Medical-HMO
445	WLP	WellPoint Inc (WLP)	Consumer, Non-Cyclical	Health Care - Services	Medical-HMO
446	THC	Tenet Healthcare Corp (THC)	Consumer, Non-Cyclical	Health Care - Services	Medical-Hospitals
447	CLX	Clorox Co/The (CLX)	Consumer, Non-Cyclical	Household Products/Wares	Consumer Products-Misc
448	KMB	Kimberly-Clark Corp (KMB)	Consumer, Non-Cyclical	Household Products/Wares	Consumer Products-Misc
449	AVY	Avery Dennison Corp (AVY)	Consumer, Non-Cyclical	Household Products / Wares	Office Supplies & Forms
450	ABT	Abbott Laboratories (ABT)	Consumer, Non-Cyclical	Pharmaceuticals	Medical-Drugs
451	AGN	Allergan Inc/United States (AGN)	Consumer, Non-Cyclical	Pharmaceuticals	Medical-Drugs
452	BMJ	Bristol-Myers Squibb Co (BMJ)	Consumer, Non-Cyclical	Pharmaceuticals	Medical-Drugs
453	FRX	Forest Laboratories Inc (FRX)	Consumer, Non-Cyclical	Pharmaceuticals	Medical-Drugs
454	JNJ	Johnson & Johnson (JNJ)	Consumer, Non-Cyclical	Pharmaceuticals	Medical-Drugs
455	LLY	Eli Lilly & Co (LLY)	Consumer, Non-Cyclical	Pharmaceuticals	Medical-Drugs
456	MRK	Merck & Co Inc (MRK)	Consumer, Non-Cyclical	Pharmaceuticals	Medical-Drugs
457	PFE	Pfizer Inc (PFE)	Consumer, Non-Cyclical	Pharmaceuticals	Medical-Drugs
458	MYL	Mylan Inc/PA (MYL)	Consumer, Non-Cyclical	Pharmaceuticals	Medical-Generic Drugs
459	PRGO	Perrigo Co (PRGO)	Consumer, Non-Cyclical	Pharmaceuticals	Medical-Generic Drugs
460	ACT	Actavis Inc (ACT)	Consumer, Non-Cyclical	Pharmaceuticals	Medical-Generic Drugs
461	ABC	AmerisourceBergen Corp (ABC)	Consumer, Non-Cyclical	Pharmaceuticals	Medical-Whsle Drug Dist
462	CAH	Cardinal Health Inc (CAH)	Consumer, Non-Cyclical	Pharmaceuticals	Medical-Whsle Drug Dist
463	MCK	McKesson Corp (MCK)	Consumer, Non-Cyclical	Pharmaceuticals	Medical-Whsle Drug Dist
464	ESRX	Express Scripts Holding Co (ESRX)	Consumer, Non-Cyclical	Pharmaceuticals	Pharmacy Services

Table 5 - Tickers, company names, sectors, industries, and sub-industries of stocks used in this article.

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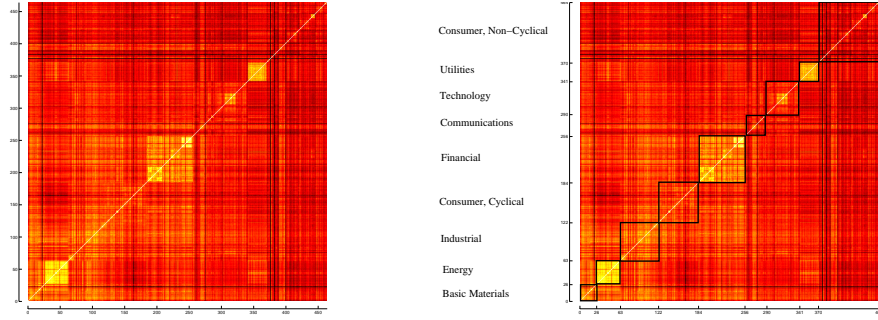


Fig. 1. Heat map of the correlation matrix of stocks (left figure), and with the sectors highlighted (right figure). Higher correlations are represented by brighter colors, and lower correlations are represented by darker colors.

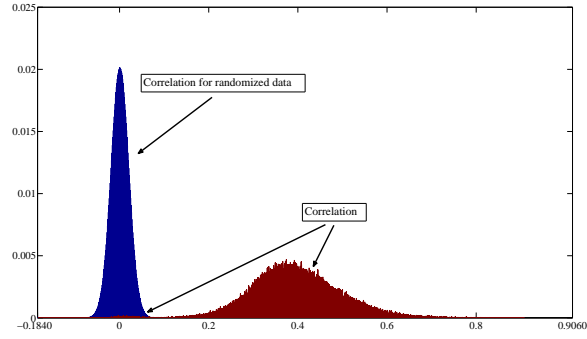


Fig. 2. Histograms for the correlation matrix and for the correlation matrices obtained with 1,000 simulations with randomized data.

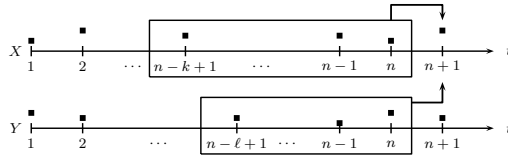


Fig. 3. Schematic representation of the Transfer Entropy $T_{Y \rightarrow X}$.

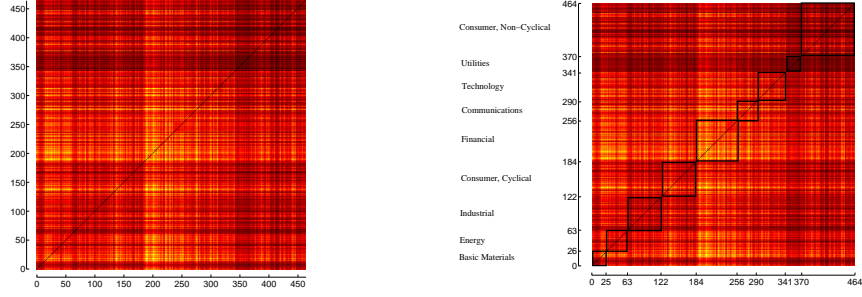


Fig. 4. Heat map of the Transfer Entropy matrix of stocks (left figure), and with the sectors highlighted (right figure). Higher values of TE are represented by brighter colors, and low values of TE are represented by darker colors.

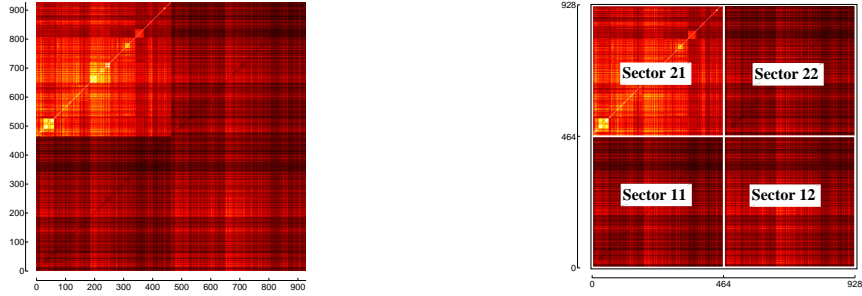


Fig. 5. Heat map representations of the expanded Transfer Entropy (TE) matrix based on lagged and original variables (left graph), and with the four sectors highlighted (right graph).

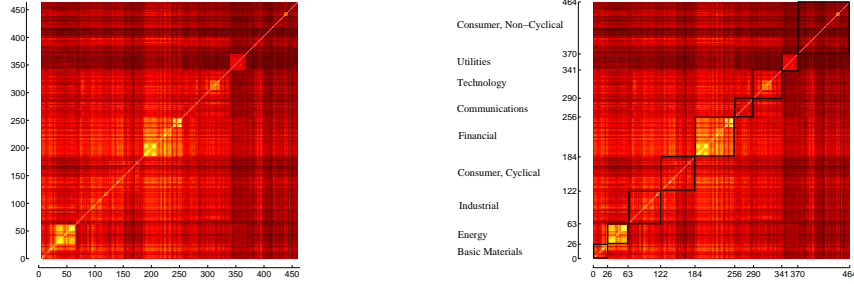


Fig. 6. Heat map representations of the Transfer Entropy (TE) matrix from lagged to original variables, sector 21 (left figure), and with the sectors highlighted (right figure). Higher values of TE are represented by brighter colors, and lower values of TE are represented by darker colors.

Fig. 7. Scatter plot for the correlations between stocks on the same day and with the TE from lagged stocks to original ones. **This figure is absent in this version of the article, since it is very heavy in terms of bits.**

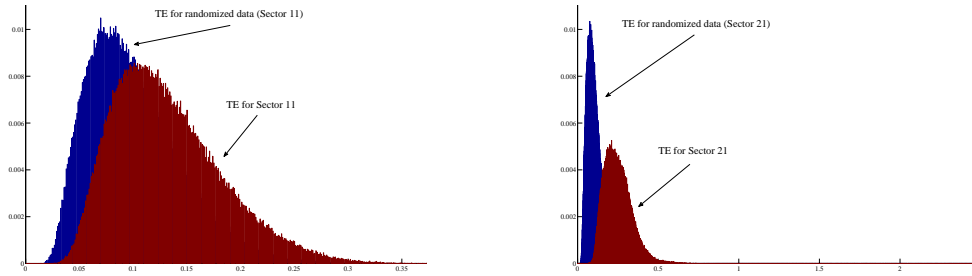


Fig. 8. Histograms for the TE matrix and for the TE matrices obtained with 10 simulations with randomized data. The left graph shows the results for sector 11 and the right graph displays results for sector 21.

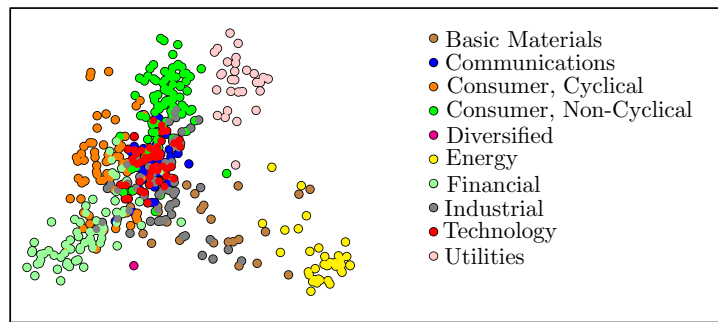


Fig. 9. Two dimensional representation of the stocks as nodes in coordinates that simulate the distances between them, based on correlation.

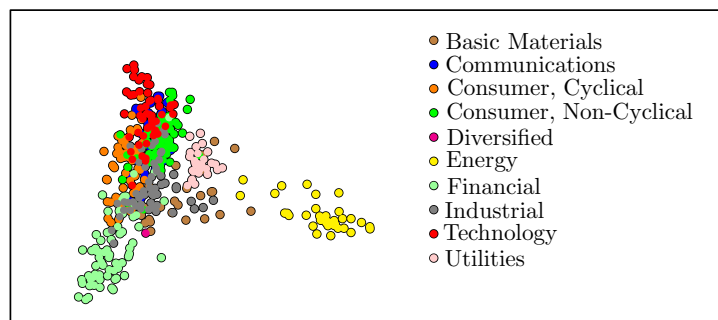


Fig. 10. Two dimensional representation of the stocks as nodes in coordinates that simulate the distances between them, based on Transfer Entropy.

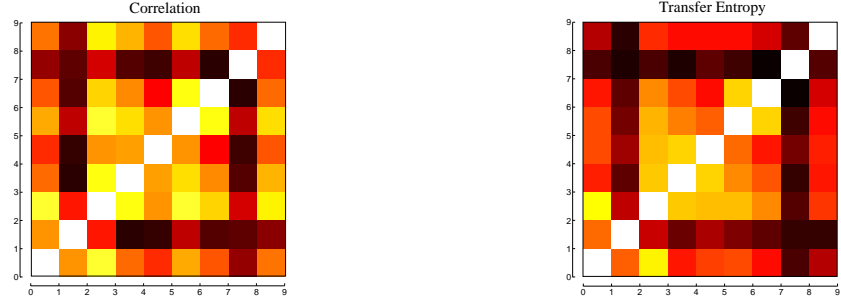


Fig. 11. Correlation (left graph) and Transfer Entropy (right graph) for the sectors, obtained from aggregate data. The order of sectors is the following: 1 - Basic Materials, 2 - Energy, 3 - Industrial, 4 - Consumer, Cyclical, 5 - Financial, 6 - Communications, 7 - Technology, 8 - Utilities, 9 - Consumer, Non-Cyclical.

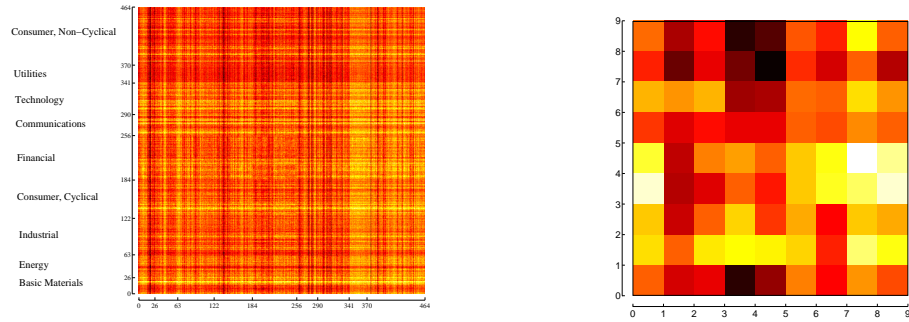


Fig. 12. Heat map representations of the Excess Transfer Entropy matrix from lagged to original variables (left figure), and for aggregate data on sectors (right figure). Higher values of Excess TE are represented by brighter colors, and lower values of Excess TE are represented by darker colors.

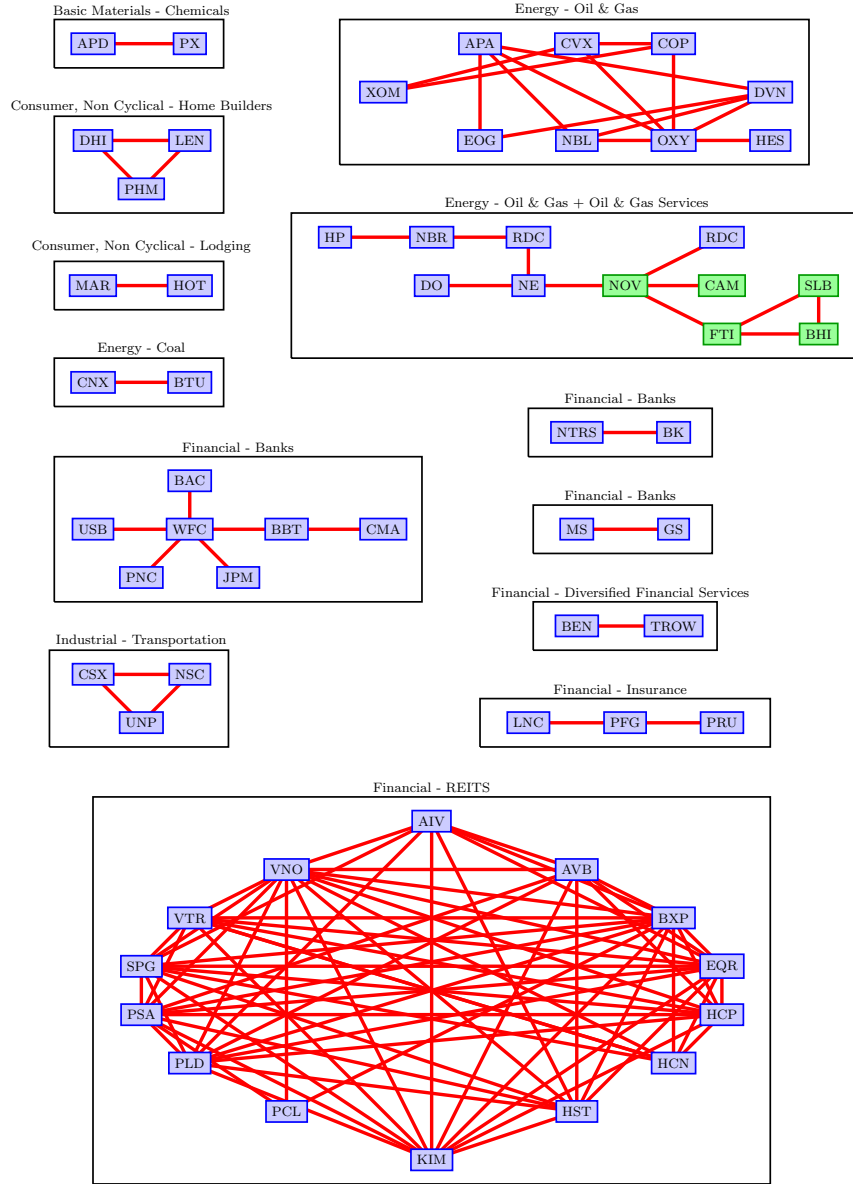


Fig. 13. Asset graph based on correlation at threshold 0.8.

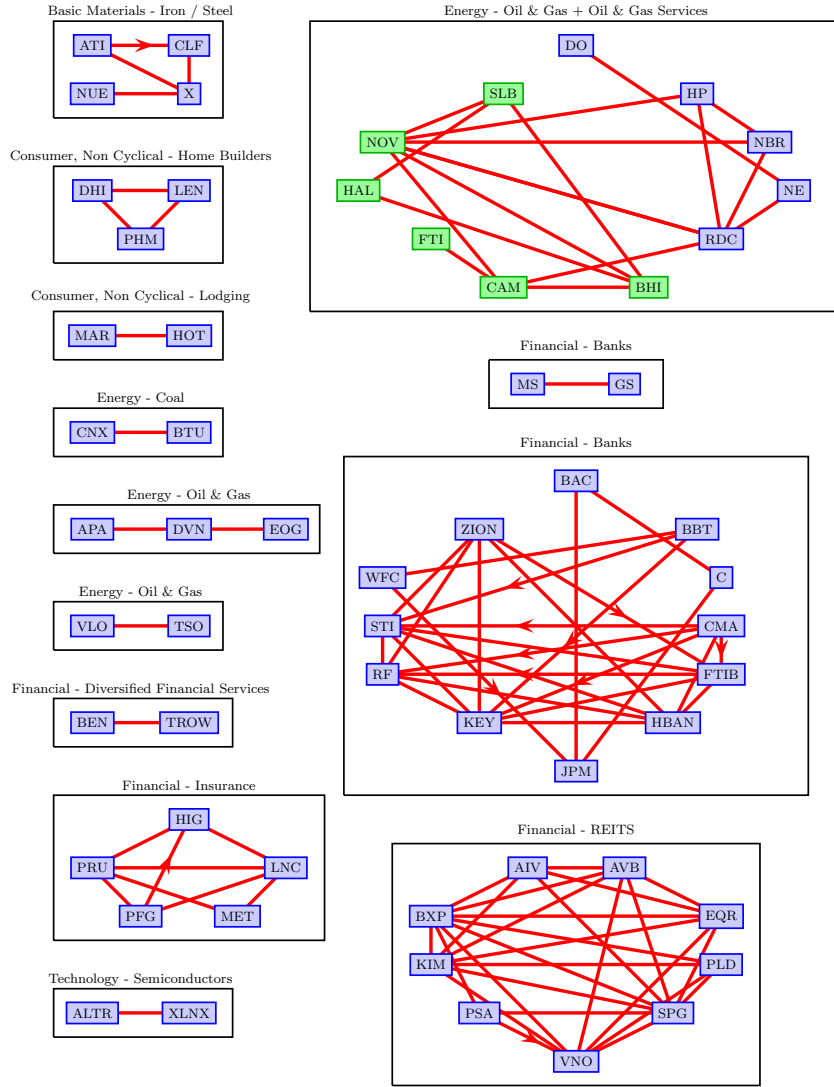


Fig. 14. Asset graph based on Transfer Entropy at threshold 0.7.

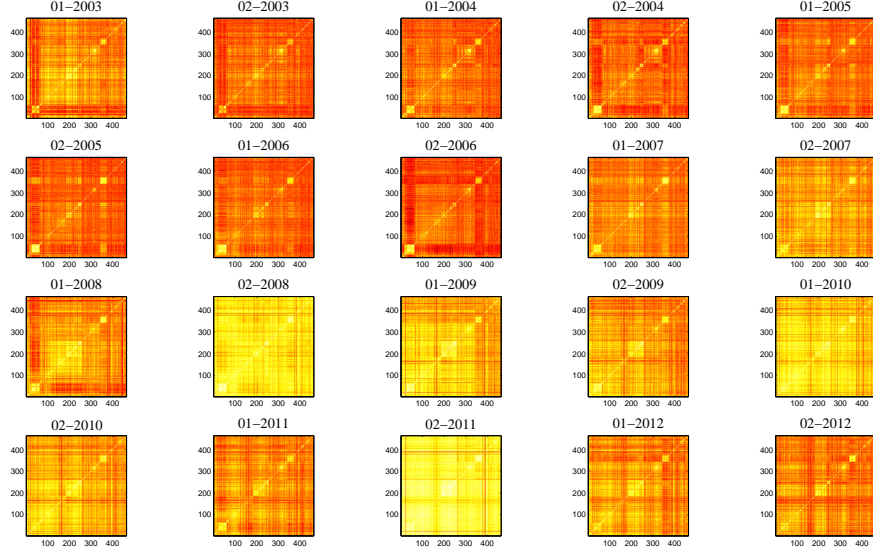


Fig. 15. Heat map of the correlation matrices according to semester and year.

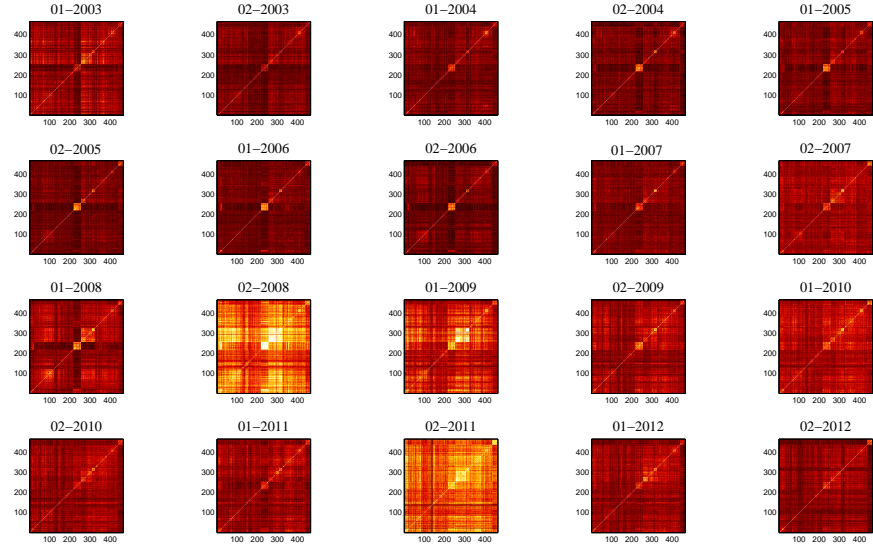


Fig. 16. Heat map of the TE matrices according to semester and year.

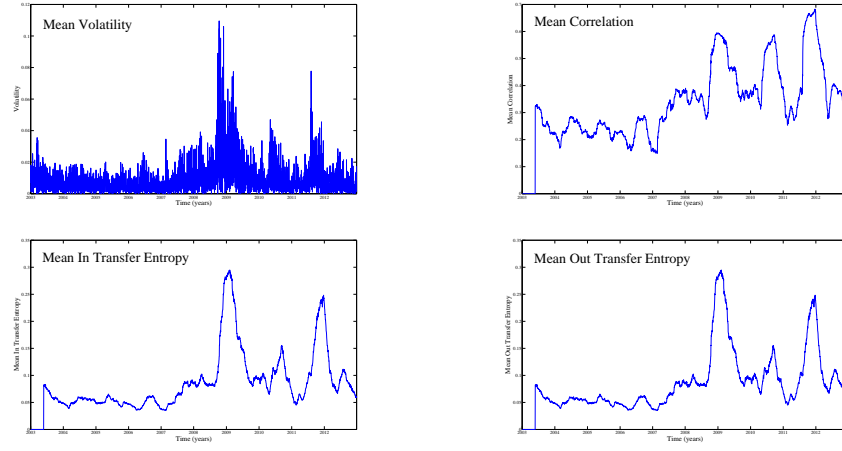


Fig. 17. Mean volatility, mean correlation, mean in Transfer Entropy, and mean out Transfer Entropy of the stocks in time. Except for mean volatility, data start at day 101.

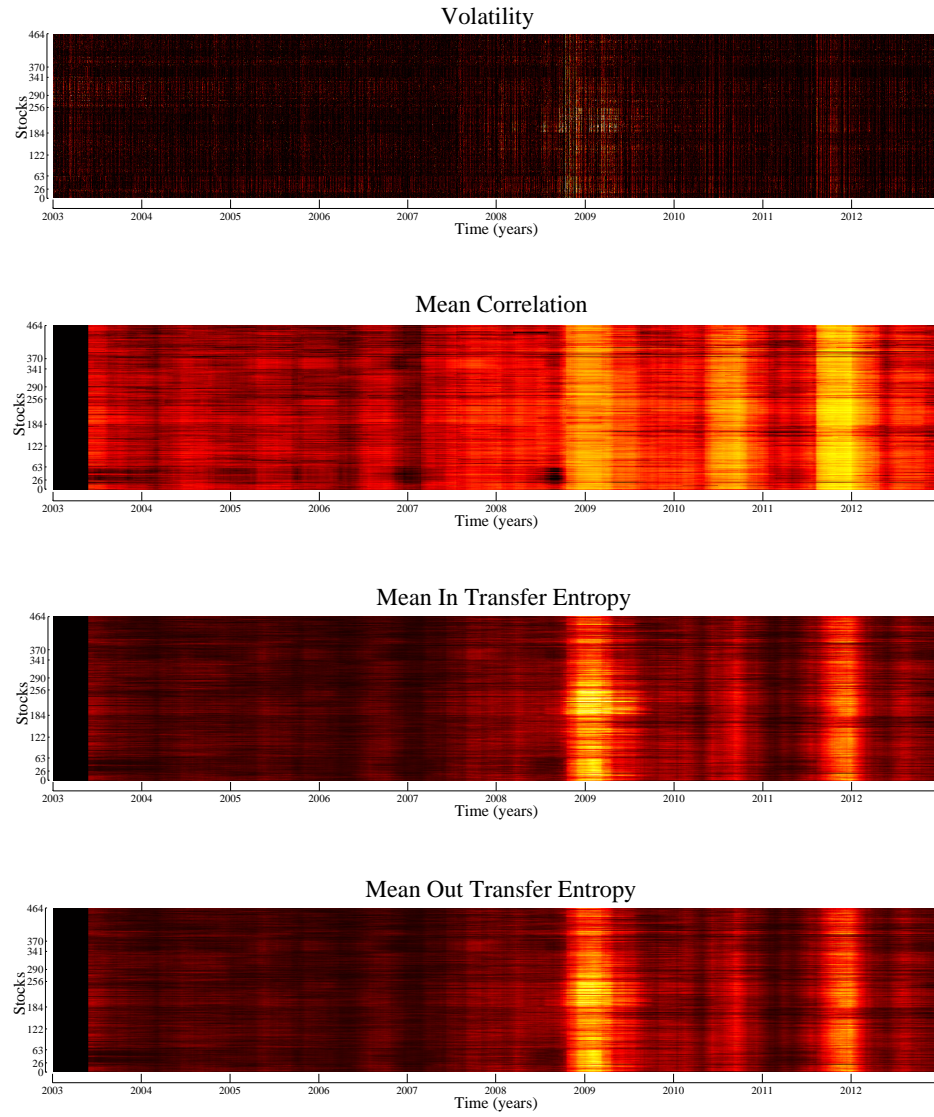


Fig. 18. Heat maps of volatility, mean correlation, mean in Transfer Entropy, and mean out Transfer Entropy according to stocks in time. Except for volatility, data start at day 101.

Fig. 19. The spread of a volatility shock among the stocks in the sample in time. The axis that goes from 0 to 464 represents the stocks, the axis that goes from 0 to 8 represents the number of days from the occurrence of the first shock (at day 1), and the vertical axis represents the volatility of each stock. **This figure is absent in this version of the article, since it is very heavy in terms of bits.**

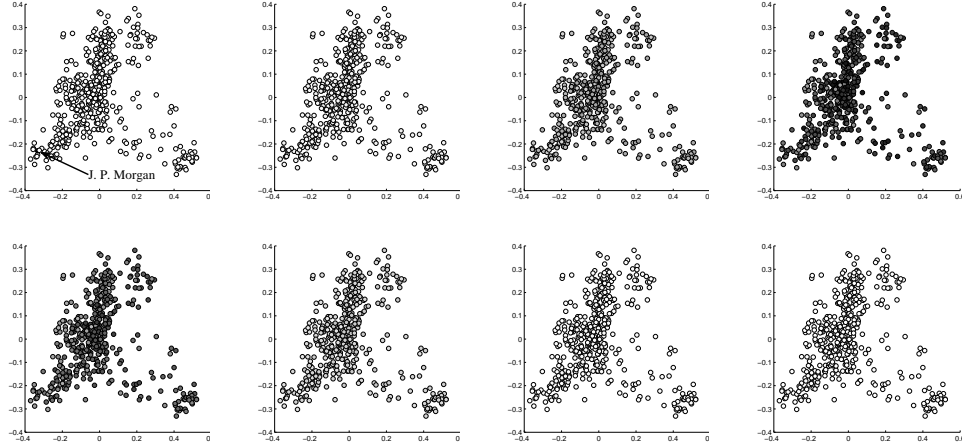


Fig. 20. The spread of a volatility shock starting with the stocks of the J. P. Morgan bank when viewed on the network of stocks built from correlation. Darker dots represent higher volatilities and brighter dots represent lower volatilities.

Fig. 21. The spread of a volatility shock among the stocks in the sample in time. The axis that goes from 0 to 464 represents the stocks, the axis that goes from 0 to 8 represents the number of days from the occurrence of the first shock (at day 1), and the vertical axis represents the volatility of each stock. The first graph represents a shock of intensity 0.1 to the entire system of stocks, the second and third graphs represent a shock of the same intensity, but now applied to the Financial and the Technology sectors, respectively. **This figure is absent in this version of the article, since it is very heavy in terms of bits.**

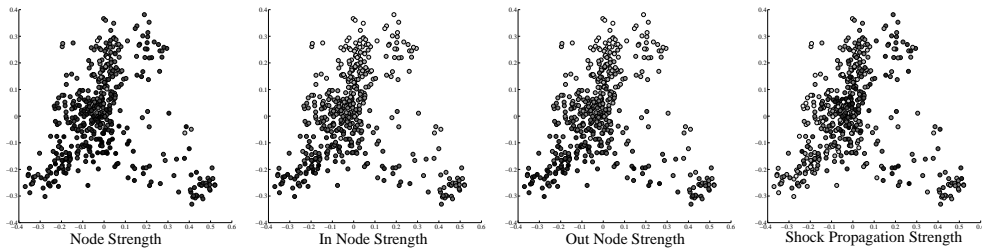


Fig. 22. Node Strength, In Node Strength, Out Node Strength, and Shock Propagation Strength represented over a network built from correlations. Darker colors represent higher values of the measures and brighter colors represent lower values of the measures.